MODELLING THE UK PERENNIAL ENERGY CROP MARKET

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Declaration

I declare that this thesis was composed by myself, that the work contained herein is my own except where explicitly stated otherwise in the text, and the work has not been submitted for any other degree or professional qualification.

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Abbreviations and units

Agent-based model	ABM
Annual equivalent value	AEV
Contract for Difference	CfD
Methane	CH_4
Combined heat and power	CHP
Carbon dioxide	CO_2
Carbon dioxide equivalent	CO_2e
Consumer price index	CPI
Direct land use change	dLUC
Exajoule (10^{18} joules)	EJ
Electricity Market Reform	EMR
Fixed operation and maintenance	FOM
General Algebraic Modelling Systems	GAMS
Greenhouse gas	GHG
Geographic information system	GIS
Gigajoule (10^9 joules)	GJ
Gigawatt-hour (10^9 watt-hours)	GWh
Hectare	ha
Indirect land use change	iLUC
Potassium	K
Kilogram	kg
Kilo hectare (10^3 hectares)	kha
Kilometre	km
Kilowatt (10^3 watts)	kW

Low heating value	LHV
Linear programme	LP
Mega hectare (10^6 hectares)	Mha
Mega tonne (10^6 tonnes)	Mt
Megawatt (10^6 watts)	MW
Megawatt-hour (10^6 watt-hours)	MWh
Megawatt-hour of electricity	MWh_e
Megawatt-hour of feed fuel	MWh_f
Megawatt-hour of installed plant capacity	MWh_i
Nitrogen	N
Oven dry tonnes	odt
Oilseed rape	OSR
Phosphorous	P
Petajoule (10^{15} joules)	PJ
Positive mathematical programming	PMP
Renewable Obligation	RO
Renewable Obligation Certificate	ROC
Soil organic carbon	SOC
Short-rotation coppice	SRC
Terawatt-hour (10^{12} watt-hours)	TWh
Tonne	t
Tonnes of fuel produced	t_p
Tonnes of fuel supplied	t_s
Variable operations and maintenance	VOM
Risk-aversion parameter	φ

Thesis abstract

Biomass produced from perennial energy crops, Miscanthus and willow or poplar grown as short-rotation coppice, is expected to contribute to UK renewable energy targets and reduce the carbon intensity of energy production. The UK Government has had incentives in place, targeting farmers and power plant investors to develop this market, but growth has been slower than anticipated. Market expansion requires farmers to select to grow these crops, and the construction of facilities, such as biomass power plants, to consume them. Farmer behaviour and preferences, including risk-aversion, are believed to be important to crop selection decisions. Existing research estimating the total potential resource has either only simplistically considered the farmer decision-making and opportunity costs, or has not considered spatial variability. No previous work has modelled the contingent interaction of farmers' decisions with the construction of biomass facilities.

This thesis provides an improved understanding of the behaviour of the perennial energy crop market in the UK, by addressing these limitations, to understand the spatial and temporal dynamics of energy crop adoption. It attempts to determine the factors that govern the rate and level of adoption, to quantify the greenhouse gas abatement potential, and to assess the cost effectiveness of policy mechanisms. A farm-scale mathematical programming model was implemented to represent the crop selection of a risk-averse farmer. This was applied using spatially specific data to produce maps and cost curves economic supply, for the UK. To represent the contingent interaction of supply and demand within the market, an agent-based model was then developed. The results indicate that perennial energy crop supply may be substantially lower than previously predicted, due to the time lags caused by the spatial diffusion of farmer adoption. The model shows time lags of 20 years, which is supported empirically by the analogue of oilseed rape adoption. Results from integrating a greenhouse gas emissions balance shows that directly supporting farmers, via establishment grants, can increase both the carbon equivalent emissions abatement potential and cost effectiveness of policy measure. Results also show a minimum cost of carbon abatement is produced from scenarios with an intermediate level of electricity generation subsidy. This suggests that there is a level of support

for electricity generated from energy crops that reduces emissions in the most cost effective manner.

Lay summary

An increasing amount of renewable energy is expected to be obtained from recently grown plants, termed biomass. Some of this biomass will be produced from dedicated crops grown specifically as a source of energy. The two main energy crops in the UK are Miscanthus, a type of grass which can grow to over 3 metres annually; and short-rotation coppice, a technique where trees species such as willow or popular are grown as a coppice and harvested every 3 or 4 years. The goal is to help to meet the UK's renewable energy targets and to reduce the greenhouse gas emission associated with energy production. To encourage the development of a market in these energy crops, the UK Government has had policies in place to support both farmers who grow the crops, and the operators of the power stations that consume them, but so far the uptake has been slower than anticipated. For the market to expand, farmers need to decide to grow these crops, and also the facilities to consume them must be built. The two decisions are interdependent, as without a market farmers are unlikely to grow the crops, requiring the power stations to have been constructed. While, at the same time, the power stations will not be built without the belief that they can obtain supply from farmers. This has been termed the 'chicken and egg' problem of the energy crop market.

This thesis provides an improved understanding of how the energy crop market in the UK may develop, by modelling the behaviour of many individual farmers and investors in biomass power stations. The aim is to understand the factors that govern the rate and level of market uptake, to quantify the reductions in greenhouse gas emissions that are possible, and to assess the cost effectiveness of different policy measures. Initially, a model of an individual farmer's decision-making, including risk-aversion, was developed. This farm-scale model was used with crop yields that are specific to each location across the UK, allowing maps of economic supply to be produced, at different energy crop prices. To represent the interaction of supply and demand, i.e. the 'chicken and egg' problem, a model representing the market as many individuals making independent decisions and interacting with each other was developed. This type of model is known as an agent-based model. The results indicate that energy crop supply may be lower than previously published, due to the delays in full adoption caused by differences in farmers' behaviour, with only a small proportion of farmers prepared to be innovative. The model shows time lags of 20 years, which is supported by historical data on the adoption of oilseed rape from the 1970s. The greenhouse gas emissions and total cost of subsidies were calculated for a number of different support policies and rates. The results showed that by directly supporting farmers there was an increase in the reduction in emission of greenhouse gases and also an increase in the cost effectiveness. Other results showed that the highest cost efficiency was seen at in scenarios with an intermediate level of electricity generation subsidy.

CHAPTER ONE

INTRODUCTION

1.1 Rationale

The world faces the challenge of providing for increasing energy demand in an economic and environmentally sustainable manner (IEA, 2012a). In the UK, the energy challenge is manifesting itself in increasing political and public concern about the national energy mix and rising prices (BBC News, 2013; Sandle & Holton, 2013). The UK's electricity generation sector has existing coal and nuclear plants that are reaching the end of their lives, reducing generation capacity (Ofgem, 2013a); while electricity demand is projected to rise gradually (National Grid, 2012). As a result, spare capacity in the UK electricity market is due to reduce over the next few years (Ofgem, 2012a). New infrastructure must seek to fill the potential gap between future electricity supply and demand, estimated to require £110 billion of investment over the next 10 years (HM Government, 2012). The UK Government sets the overall framework for investment in energy infrastructure, but it is the private sector that will then determine where and when it will occur.

Biomass is a source of renewable energy that could help to meet these challenges. In a global context, it is already the largest source of renewable energy, and is expected to expand to 160 EJ year^{-1} in 2050 from 50 EJ year^{-1} today (IEA, 2012b). In the UK, it could supply 8-11% of the UK's total primary energy demand by 2020 (DfT *et al.*, 2012), and form a significant part of meeting the legally binding target of 15% of its energy consumption from renewable sources (DECC, 2011a). The greatest growth in UK domestic biomass supply is expected to come from agricultural residues and energy crops (DfT *et al.*, 2012). The consensus from previous research is that the potential energy crop area in the UK is around 1 to 2 Mha in 2020 and 2030 (Gill *et al.*, 2005; DEFRA, 2007; Aylott *et al.*, 2008; E4tech, 2009; Bauen *et al.*, 2010; Thomas *et al.*, 2013a). It has also been suggested that between 930 and 3630 kha of land in England and Wales could be used for growing dedicated perennial energy crops, without impinging on food production (DfT *et al.*, 2012).

Biomass from perennial energy crops is currently converted into heat, electricity or both; sometimes wood pellets are produced, to aid transport and distribution. There is also the prospect of commercial bio-refineries able to convert the lignocellulose from perennial energy crops into liquid biofuels, sometimes termed second-generation biofuels (Janda *et al.*, 2011; Hayes, 2013). It has been suggested that 40 billion gallons of second-generation biofuel could be sustainably produced annually in the US by 2035 (UCS, 2013), primarily from energy crops, equivalent to 30% of 2011 US gasoline demand (EIA, 2013). Second-generation biofuels are also suggested to form a significant component of the UK's least cost energy system to 2050 (Jablonski *et al.*, 2010).

These perennial energy crops, Miscanthus and willow or poplar grown as short-rotation coppice (SRC), have been grown in the UK since around 1996 (Aylott & McDermott, 2012). However, uptake has been limited, with a total area of only 11 kha in 2011, with the planting rate dropping to only 0.5 kha year^{-1} in the period 2008-11 (DEFRA & Government Statistical Service, 2013). Although there is currently no target for areas of these crops, 350 kha by 2020 was suggested in the Biomass Strategy (DEFRA, 2007), but it is now expected that the actual figure will be much lower (Aylott & McDermott, 2012). The low uptake is underlined by the existence of support policies related to energy crops, targeted at both the farmers and the energy producers. Farmers in England have had access to grants covering 50% of the establishment costs for planting Miscanthus or SRC (Natural_England, 2009); renewable electricity generators have been able to receive support under the Renewable Obligation (RO) mechanism (Ofgem, 2013b); and renewable heat technologies are supported by the Renewable Heat Incentives scheme (DECC, 2011b).

Both economic and behavioural factors have been proposed as being involved in farmers' decisions to adopt energy crops. A number of studies have looked at the economic aspects of energy crops. Some have taken an estimate of the annual land rental charge to account for the foregone opportunity to make greater returns from other activities, or opportunity costs (Monti *et al.*, 2007; E4tech, 2009; Bauen *et al.*, 2010). The other approach commonly taken is to compare annual gross margins of conventional crops with an equivalent annualised value for the perennial energy crops (Bell *et al.*, 2007; Styles *et al.*, 2008; Turley & Liddle, 2008; Clancy *et al.*, 2012; Taylor *et al.*, 2013). Another method, taken by Sherrington & Moran (2010), is to use a farm-scale economic model to investigate the implicit potential uptake of perennial energy crops, in this case selecting activities to maximise gross margin. The results for these studies show, that based on the economic case, energy crops should have been adopted more widely, leading to support for the existence of other barriers to adoption. Barriers such as establishment costs, delays in cash flows, lack suitable machinery, awareness and educational barriers, long-term commitment of land, and constraints of existing farm businesses have all been identified (Sherrington *et al.*, 2008; Bocquého & Jacquet, 2010; Aylott & McDermott, 2012; Gedikoglu, 2012; Qualls *et al.*, 2012; Glithero *et al.*, 2013). The 'chicken and egg' problem also appears a significant barrier; farmers are not willing to grow the crops without a more mature market and potential investors are not willing to develop the plants and technologies that are required to create the demand and so establish the market (Sherrington *et al.*, 2008). The cyclic contingent behaviour between farmers and plant investors increases the complexity of the overall system, making analysis more difficult.

Energy crops compete for land resource with other potential land uses, and so have the potential to have positive and negative impact on a range of environmental factors, e.g. greenhouse gas (GHG) emissions, soil organic carbon (SOC), biodiversity and water resources (St. Clair *et al.*, 2008; Hillier *et al.*, 2009; Rowe *et al.*, 2010; Thomas *et al.*, 2013b). As a result, increased uptake of these crops will also be relevant to other policy objectives for the provision of ecosystem services. Biomass energy is sometimes assumed or stated as having zero net emissions of carbon dioxide (Al-Mansour & Zuwala, 2010; Bertrand, 2013), or given a zero emissions factor (HM Treasury & HM Revenue & Customs, 2010). However, although the carbon released during the energy production has been captured during plant growth, there are potential direct and indirect sources of emissions (Bullard & Metcalfe, 2001; Bauer, 2008; St. Clair *et al.*, 2008; Cherubini & Jungmeier, 2009; Wiltshire & Hughes, 2011; Perilhon *et al.*, 2012). Direct emissions relate to the production, transport, handling and processing lifecycle stages; while indirect emissions can occur due to land use change potentially causing SOC changes. These crops, therefore, could form a potentially important component in reducing the carbon intensity of energy production, but occur with a number of trade-offs that need to be understood.

There has been considerable controversy over biofuels, sometimes termed first-generation, that are produced from food crops, vegetable oils (e.g. rapeseed, sunflower or palm) or starch (e.g. wheat, maize or sugarcane). Concerns have been raised that they compete with food production, which may indirectly result in the conversion to agricultural production of other land, including native ecosystems. The GHG emissions caused by such indirect land-use change (iLUC), potentially outweighs the direct emissions reductions (Searchinger *et al.*, 2008; Haberl *et al.*, 2012). Further, the competition with foods was held responsible for the food price spike seen in 2007-08 (Eide, 2008; Mitchell, 2008). However, despite continued increases in bioenergy, prices then returned to more sustainable levels, suggesting other factors may have been involved (Rathmann *et al.*, 2010; Slade *et al.*, 2011). Although sustainable and unsustainable biomass production chains may occur (Environment Agency, 2009; ERP, 2011), some first-generation biofuel production processes have been shown to provide net emissions reduction, as well as other benefits (Horta Nogueira *et al.*, 2013). Second-generation biofuels do not compete as directly with food for feedstock, and are able to process more of the plant biomass, by using the ligno-cellulosic material (Janda *et al.*, 2011). Using biomass from sources such as crop and forestry residues, waste, and sustainably grown perennial energy crops, has the potential to provide the benefits, without the undesirable impacts (Tilman *et al.*, 2009; Potters *et al.*, 2010). Increased agricultural productivity is anticipated to make land available for energy crop production, so avoiding iLUC (Goldemberg *et al.*, 2008; Slade *et al.*, 2011).

The energy crop market is a complex system involving human decision-making by many individuals, working within a policy and ecological environment. The social, economic and ecological aspects of the systems are strongly coupled, making our understanding of any aspect in isolation impossible. The potential benefits and drawbacks of the adoption of these crops at scale requires that we attempt to understand this coupling more fully, and to suggest ways that net societal benefits can be maximised. Related policies are currently in flux (DECC, 2013a), increasing the need for greater scientific understanding of these trade-offs and analysis on which measures are appropriate and cost-effective. Furthermore, the reasons for the lower than anticipated uptake of these crops to date (Aylott & McDermott, 2012) needs to be understood, and potential measures identified that could help to stimulate the market.

The research undertaken in this thesis addresses several gaps identified in the existing research, including the following aspects:

- The behavioural aspects of adoption, including risk-averse farmer decision-making, believed to be important for energy crop uptake (Sherrington *et al.*, 2008; Aylott & McDermott, 2012; Glithero *et al.*, 2013).
- The contingent interaction between supply and demand. Previous studies on the energy crop markets either optimised demand where supply is exogenously given (Dunnett *et al.*, 2008; Schmidt *et al.*, 2010; Yagi & Nakata, 2011; Akgul *et al.*, 2012; Alex Marvin *et al.*, 2012), or investigated the supply distribution for an assumed level of demand (Aylott *et al.*, 2010; Bauen *et al.*, 2010; Thomas *et al.*, 2013a).
- An endogenous representation of the market price, which is only possible by modelling supply and demand within the market, not something previously attempted.
- An assessment of the costs of carbon abated from the market. Although previous GHG emissions balances have been conducted (St. Clair *et al.*, 2008; Cherubini & Jungmeier, 2009; Perilhon *et al.*, 2012), these have not been able to look at costs accounting for variation in uptake.
- Analysis to explain historical behaviour, or to simulate potential future scenarios.
- An impact analysis of policy decisions on adoption and therefore GHG abatement.

1.2 Aims and objectives

This research spans natural and social science elements, and methodological approaches, that further our understanding of the coupling between energy, land-use and the environment created by the adoption of energy crops. It does this by addressing the following research questions:

- What previous land-uses, and associated farm types, will energy crops displace?
- What is the scale of the UK energy crop market, and how does this compare to the UK Government's targets?
- What are the likely spatial and temporal dynamics of the market development?
- What are suitable policies for stimulating the market? How does varying subsidies impact market development and potential emissions reductions?
- What other factors are relevant to the development of the energy crop market?
- What mechanisms could be used to encourage development of the energy crop market, e.g. reducing farmer perceptions of barriers to adoption through farmer education?
- How can the biomass market develop in a manner that generates cost-efficient emissions reductions?

The technical or methodological objectives are addressed with the use of an agent-based model (ABM), to represent the complex social-ecological system of the energy crop market. ABMs allow the system behaviour to emerge through the dynamic agent interaction with one another and the environment (Rounsevell *et al.*, 2012). This approach is suitable for the development of a model of the energy crop market, as ABMs allow the spatial and dynamic behaviour of complex systems to be investigated (Zimmermann *et al.*, 2009), and supports the two-way interaction between micro and macro scales (Happe, 2004), features which many other approaches find intractable.

Applying an ABM to a system combining interacting social and environmental elements, or other land-use modelling, over a large geographic area with a relatively small grid size, is demanding both in data and computational requirements (Kellermann & Balmann, 2006; Dunnett *et al.*, 2008; Chen *et al.*, 2010). Consequentially, this type of approach has typically been applied either to idealised cases or to smaller areas. The objective in this thesis is to represent the UK energy crop market at a high spatial resolution (1km^2), so as to capture variation in agricultural resources, due to soil, climate and topography. The computational requirements arising from the complexity of the system combined with such a spatial scale means that parallel computing facilities are required. The techniques, knowledge and potentially model components developed, could be used to investigate the dynamics on other coupled social-ecological systems.

1.3 Thesis Structure

The thesis consists of six chapters, starting with an introductory chapter (Chapter One) and finishing with overall conclusions (Chapter Six). The remaining four chapters are written and presented as a series of papers, all of which have been published by peer reviewed journals (Alexander & Moran, 2013; Alexander *et al.*, 2013, 2014a, 2014b). A full copy of each of these papers is included as an appendix. These chapters can therefore be read independently. However, each builds on the previous to gain further insights into the dynamic behaviour and impact of the UK energy crop market. The stages of the work and their relationship to one another are shown in Figure 1-1, including the structure of chapters and the associated journal articles.

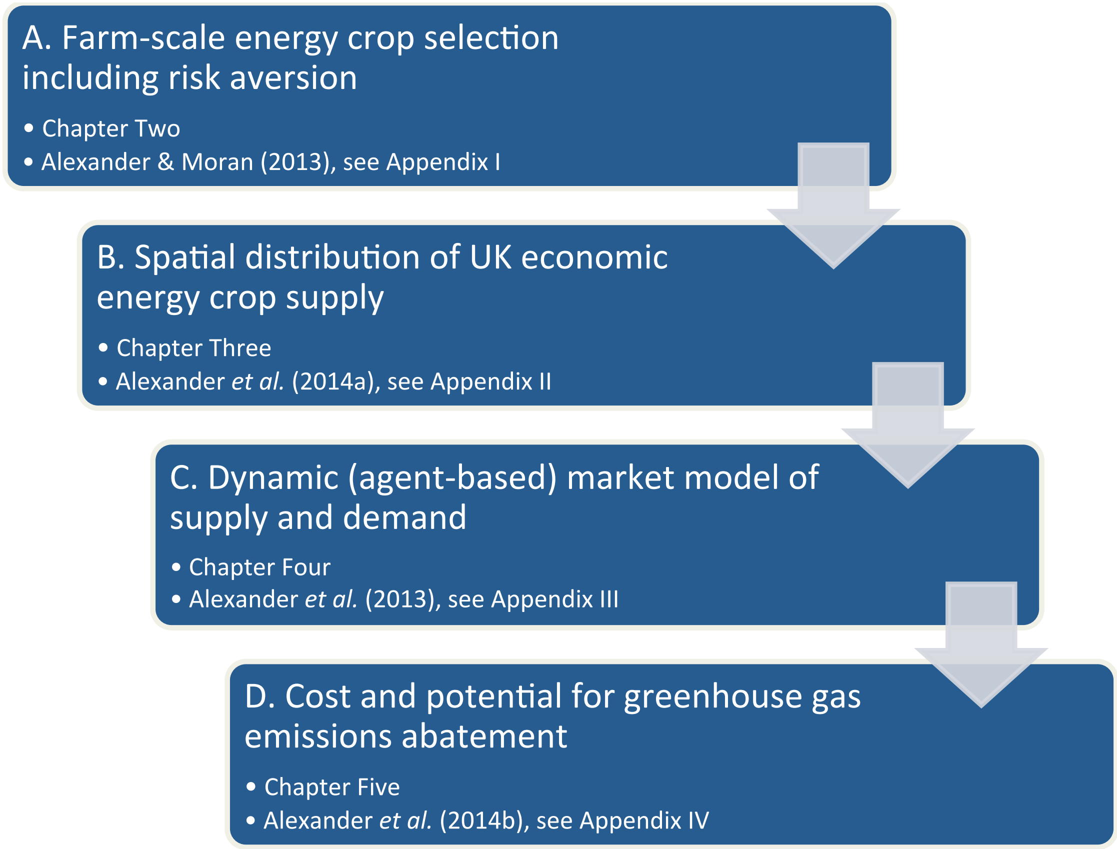


Figure 1-1: Stages of the work completed, with associated thesis chapter and publication structure.

Chapter Two presents the development, validation and use of a farm-scale model, including energy crops, representing an individual farmer's crop selections under risk-aversion (Alexander & Moran, 2013). This farm-scale model was then used with spatially specific data, at a 1km^2 resolution, to improve understanding of the total economic UK perennial energy crop supply, and the geographic and temporal distribution, under climate change scenarios, as described in chapter Three (Alexander *et al.*, 2014a). The spatial analysis of supply implicitly assumes demand in all areas, at an exogenously supplied farm-gate energy crop price. This model is therefore unable to represent variations in transport distances or costs. Further, the contingent behaviour between demand being created through investment in facilities to consume the crops, and farmers choosing to grow them, is not represented, nor is the behavioural aspects of farmers' adoption (i.e. diffusion of innovation). Chapter Four describes an ABM that was developed to provide a greater understanding of the spatial and temporal dynamics of the energy crop market and adoption scenarios (Alexander *et al.*, 2013). A detailed calculation of GHG emissions balance is presented in Chapter Five (Alexander *et al.*, 2014b), and integrated into the ABM. The model is used to calculate the total emissions abatement and cost of carbon that the market might provide, under various policy scenarios.

The model complexity increases through the thesis, as each chapter adds additional aspects. Model simplicity or parsimony, is often seen as a positive attribute, allowing for easier, less error prone, model formulation, providing a greater understand of the model's behaviour. Occam's Razor states that "plurality should not be posited without necessity", or that the hypothesis that fits the data with few assumption should be preferred. However, there is no unanimity that simple models, or theories, should always be chosen, even where the simple model are consistent with observations (Hirschman, 1984; Courtney & Courtney, 2008). Such a difference of opinion exists within the ABM community. Axelrod (2005) suggested that ABM complexity should be in the results and not the model assumption, under the acronym KISS ("Keep it simple, stupid"). In reaction, Edmonds & Moss (2005) proposed the KIDS ("Keep it descriptive, stupid") approach. KIDS involved a descriptive approach to formulating ABMs, and only simplifying if it could be shown to be justified (Edmonds & Moss, 2005).

The reason for the increasing model complexity presented in this thesis is a desire to capture variations in the system inputs or expand the boundary of the system being modelled, rather than for epistemic reasons. In Chapter Two only aggregate responses can be determined, using mean yield for an area under consideration. The extra complexity in Chapter Three arises from the need to consider the spatial variation in yields. That analysis provides an assessment of the quantity and location of energy crop supply, at an exogenous energy crop price, assuming that energy crop demand exists in all locations. Chapter Four is an attempt to endogenously represent the energy crop price, and include spatial variation in demand. To accomplish this, supply, demand, and the interactions between them needs to be represented in the model. The large number of variables arising from the spatial analysis of this system practically precludes the determination of a system optimal solution, and also would not allow for the human behavioural aspects or heterogeneity of preferences to be incorporated. The ABM implemented to represent this system necessarily results in significantly increased complexity as compared to the analysis in the previous chapter. This is in part due to the replacement of the deterministic behaviour of the previous modelling approaches with the ABMs stochastic behaviour together with the requirement to then consider variation in model results for each set of parameters. The stochastic behaviour of the model, and the range of outcomes due to path-dependence, may be reflective of actual market behaviour (Garrouste & Ioannides, 2000). Chapter Five takes the market model and uses it to examine the impact of various potential policies on emissions abatement. Additional complexity is introduced in this chapter through the calculation of GHG emissions balances and the usage of policy scenarios.

Some indication of the progression of increasing complexity between each chapter can be seen from the computational requirements at each stage. The results in Chapter Two encompass the output of a few thousand optimisations and in aggregate would take just a few minutes to run. The spatial analysis in Chapter Three runs these farm scale optimisations spatially and would take the order of a few hours to complete. The additional complexity in the ABM (Chapter Four) means each simulation takes around 10 hours to complete and due to the number of simulations the total compute time is in the order of months or perhaps a year. Due to using parallel computing facilities, the actual time taken, sometimes termed “wall-clock time”, is fortunately much lower. In Chapter Five there are a far larger number of scenarios and the total CPU compute time was measured at 1.93 million (SPECfp) hours or 220 years, including development and testing runs. Therefore, there is around a 100 times increase in compute requirements between each chapter.

The development of the farm scale model (Chapter Two) is estimated to represent 20% of the total modelling effort, with the spatial analysis (Chapter Three), a further 20%. The initial ABM development (Chapter Four) represents the largest modelling effort of the work presented in the thesis, around 35%. The remaining 25% of modelling effort was expended in the development and integration of a GHG emission balance and policy scenarios (Chapter Five).

The models and data developed and used for this work are available from the repositories https://bitbucket.org/alexanpe/farmagent and https://bitbucket.org/alexanpe/ec-data respectively.

CHAPTER TWO

IMPACT OF INCOME VARIABILITY

After article: Alexander P, Moran D (2013) Impact of perennial energy crops income variability on the crop selection of risk averse farmers. *Energy Policy*, 52, 587–596. See Appendix I.

2.1 Abstract

The UK Government policy is for the area of perennial energy crops in the UK to expand significantly. Farmers need to choose these crops in preference to conventional rotations for this to be achievable. This chapter looks at the potential level and variability of perennial energy crop incomes and the relation to incomes from conventional arable crops. Assuming energy crop prices are correlated to oil prices the results suggests that incomes from them are not well correlated to conventional arable crop incomes. A farm-scale mathematical programming model is then used to attempt to understand the affect on risk-averse farmers' crop selection. The inclusion of risk reduces the energy crop price required for the selection of these crops, due to the reduced risk with a diversified crop selection. However yields towards the highest of those predicted in the UK are still required to make them an optimal choice, suggesting only a small area of energy crops within the UK would be expected to be chosen to be grown. This must be regarded as a tentative conclusion, primarily due to high sensitivity found to crop yields, resulting in the need for the next stage of work to apply the model using spatially disaggregated data.

2.2 Introduction

Increased biomass use is expected to contribute to the UK's target to source 15% of energy from renewable sources by 2020 (DECC, 2009). To achieve these targets high growth rates are required in the biomass sector, both in the supply chain and biomass plant investment (Environment Agency, 2009). The UK Biomass Strategy identifies the prospect of part of the increased supply coming from a major expansion of UK production in perennial energy crops, potentially using 350 kha, an area equivalent of 6.5% of total arable land (DEFRA, 2007). Despite the existence of financial incentives, the area of UK perennial energy crops established has so far been comparatively limited, at around 17 kha (RELU, 2009). The low uptake of these incentives promoted the grant rate to be increased from 40% to 50% of establishment costs (DECC, 2009).

There has been a number of studies to determine and model the biophysical properties of perennial biomass crops, as well as assessing the optimal spatial locations for production given biophysical constraints, such as temperature, soil and water limitations (Price *et al.*, 2004; Andersen *et al.*, 2005; Aylott *et al.*, 2008; Richter *et al.*, 2008; Hastings *et al.*, 2009). Other research has applied environmental and socials constraints (Lovett *et al.*, 2009; Aylott *et al.*, 2010). A number of other studies have looked at the economic aspects of energy crops. Some have taken an estimate of the annual land rental charge to account for the foregone opportunity to make greater returns from other activities, or opportunity costs (Monti *et al.*, 2007; E4tech, 2009; Bauen *et al.*, 2010). The other approach commonly taken is to compare annual gross margins of conventional crops with an equivalent annualised value for the perennial energy crops (Bell *et al.*, 2007; Styles *et al.*, 2008; Turley & Liddle, 2008). Sherrington & Moran (2010) took a farm-scale economic modelling approach to investigate the implicit potential uptake of perennial energy crops, optimising across activities to maximise gross margin. The results suggested that Miscanthus should have been adopted more widely, leading to support for perceived additional risks as a barriers to adoption.

Risk has often been cited as an important factor in farmer decision-making, with studies showing that farms typically behave in a risk-averse manner (Binswanger, 1980; Oglethorpe, 1995; McCarl & Spreen, 1996; Wallace & Moss, 2002; Arriaza, 2003). Comparing predictive capabilities of alternative models showed that models which exclude risk performed poorly (Arriaza, 2003). In the case of novel crops, representing risk has been identified as being of additional importance (Styles *et al.*, 2008; Sherrington & Moran, 2010). However, to date analysis of energy crops choice including risk-aversion does not appear to have been conducted.

This chapter estimates the income variability of energy crops and their correlation to conventional crops using historic data. Farmer selection of perennial energy crops with a representation of risk-aversion is then investigated using these data. The focus will be on SRC and Miscanthus, both dedicated perennial energy crops. The chapter outlines an approach to integrate these novel crops, where the empirical data are unavailable. The significant factors in determining energy crop selection are investigated using a sensitivity analysis approach. Preliminarily conclusions are then drawn regarding the potential levels of economic growth of the energy crops in the UK. This then leads to the next stage of work, presented in Chapter Three, to apply the model to spatially and temporally disaggregated data within the UK, allowing maps of economic energy crop growth to be generated.

2.3 Materials and methods

2.3.1 Farm-scale model

Farm-scale economic modelling has a long history as a methodology to analyse decision-making, typically under conditions of competing choices for the allocation of limited resources subject to some optimisation criterion (Heady, 1954). This application represents decision-making in an arable farm type, where the optimisation criterion represents profit maximisation with constant absolute risk-aversion.

The relevant arable activities, constraints and models were implemented using GAMS (General Algebraic Modelling Systems) (Brooke *et al.*, 2010). No controlling and calibrating constraints or quotas were applied which did not represent observable constraints. McCarl & Spreen (1996) highlighted the danger of subjective constraints to "correct" model deficiencies. They give a "nominal" appearance of reality, but are actually causing the "right" solution to be observed for the wrong reason. Although rejection of such constraints may lead to models yielding excessively specialized solutions, the risk representation potentially provides for more complex and realistic behaviour. A positive mathematical programming (PMP) would provide certainty that the model could be calibrated to the observed data and be able to reproduce it (Howitt, 1995). PMP and other empirical approaches are in general not able to incorporate activities that are not within the observed base data (Arriaza, 2003). Therefore they were not appropriate for modelling of energy crops where their current novelty means sufficient observed data are unavailable. A normative mathematical programming approach was therefore selected.

An existing farm-scale linear programme (LP) implemented in Microsoft Excel was taken as a starting point (Sherrington & Moran, 2010). The same approach was implemented to represent the nine conventional arable crops [winter wheat, winter barley, spring barley, winter oats, oilseed rape (OSR), sugar beet, peas, beans, and main crop ware potatoes], for multiple fertiliser application rates. Constraints were set on land availability and crop rotation. There were no fixed labour constraints, however all operations are charged at contract rates. This implies a disincentive to take on extra effort, including an allocation for machinery cost and fuel cost. Off-farm income and single farm payments were not represented, as the absolute level of total farm income was not being investigated. It was assumed that the area was outside of a Less Favoured Area.

Expected incomes and costs were calculated using the current observed prices and rates. Evidence has been found that the single most significant farmers behaviour is associated with this price expectation (Brink & McCarl, 1978; Chavas, 2000).

A risk representation was implemented in the model, using an expected income-standard deviation approach (Hazell & Norton, 1986). Perennial energy crops have a high initial establishment costs, with payback periods of many years. They are novel crops and the farmer is unlikely to have previous experience of them on which to base their decision-making. Both these points potentially lead to a higher perception of risk. In addition the market is less well developed than for conventional crops.

2.3.2 Data

The period 1990-2009 was used for the historic dataset. Historical time series data were for conventional crop prices and yields were from the Department of Environment Food and Rural Affairs (DEFRA, 2010). Prices, input rates, yields and contractor rates were taken from the SAC farm handbook 2009/10 (SAC, 2009). All prices were calculated in 2009 terms. The Office of National Statistics was used to obtain the inflation data using the "All Items" consumer price index (CPI) inflation data (ONS, 2011). Energy price data were sourced from the Department of Energy and Climate (DECC, 2010).

2.3.3 Energy crops inclusion

Comparisons of conventional annual crops with the energy crops have to take account of the fact that the energy crops considered are perennial. Both energy crops have a high cost of establishment that takes a number of years to pay back; but have long productive lifespans. Miscanthus is harvested annually, while SRC is harvested less frequently, typically every 3 years. All these aspects need to be factored into calculating a value that can be meaningfully compared to the gross margin on annual crops.

The energy crop data have been used to calculate an annual equivalent value (AEV), this represents an annual energy crop gross margin (Bell *et al.*, 2007; Sherrington & Moran, 2010). The AEV produced can be compared to the gross margins derived for the conventional annual crops. The AEV is calculated by first determining the present value of all cash flows, by suitably discounting. The net present value of the crop is then annualised over the lifetime of the crop, using the sum of the discount factors for each year. This can be written as:

$$AEV = \left(\sum_{i}^{m} p_i y_i f_i - \sum_{j}^{n} c_j f_j \right) \Big/ \sum_{k}^{n} f_k \qquad (2\text{-}1)$$

where: p_i is the energy crop price at the year i of m harvests years; y_i is the yield of the harvest at year i; f_i is the discount factor at year i; and c_j is the total of all costs in the j year of n year crop life.

All future values were adjusted into 2009 terms using a 6% discount rate. All transactions were assumed to occur at the end of the year in which they occur. SRC plantations were assumed to be harvested every 3 years (Aylott *et al.*, 2008). The total lifespan was taken as 21 years, or 7 harvests (Bauen *et al.*, 2010). Miscanthus plantations where harvested annually starting in the second year, with a 16 years lifespan (Styles *et al.*, 2008). For a given scenario, the yields were assumed to be constant, with the exception of the first SRC harvest where the yield was reduced to 60% (Kopp, 2001). Prices are taken as farm gate prices. As a result prices may be an overestimate, although the degree would vary based on the transport costs.

The farm-gate price was also assumed constant over the crop lifetime. As a result the summations in equation (2-1) can be rearranged to be independent of assumed constant base price and yield. They can then be pre-calculated and used for any price or yield situation to determine the associated AEV or gross margin. Such an approach reduces the data and computational requirements in the optimisation model, as it can be done once for many models in a pre-optimisation step.

The Energy Crops Scheme offers grants to farmers in England for establishing Miscanthus and SRC for their own energy use or to supply power stations. The energy crop grants paid 50% of all eligible costs incurred, with the scheme available to applicants until August 2013 (Natural_England, 2009). Previously there had been a European Union energy crop payment of €45 ha^{-1}, however this is no longer available for new planting (Natural_England, 2009). Fertiliser was taken as only being applied to SRC at planting and after each harvest (Bell *et al.*, 2007), in part as the physical size of the crop and available equipment makes applications at other stages problematic (DEFRA, 2004).

The published energy crop costs differ, for example SRC establishment costs in 2007 terms vary from £1338 ha^{-1} (Valentine *et al.*, 2008), to £1996 ha^{-1} (Bauen *et al.*, 2010). However, as shown by Bauen *et al.* (2010), the sensitivity of energy crop cost of product to establishment costs is relatively low. The more conservative figures and structure were followed from Bauen *et al.* (2010). These 2007 figures were future valued to 2009 terms using the CPI inflation data (ONS, 2011). The resulting values used are displayed in Table 2-1.

Table 2-1: Prices and rates for energy crops, in 2009 £ terms, based on Bauen *et al.* (2010).

Item	Unit	SRC	Miscanthus
Establishment Cost	£ ha^{-1}	2113	1887
Establishment Grant	£ ha^{-1}	1057	943
Removal	£ ha^{-1}	529	106
Fixed overhead	£ ha^{-1} $year^{-1}$	92	92
Fertiliser	£ ha^{-1} $application^{-1}$	26	0
Harvesting Cost	£ ha^{-1} $harvest^{-1}$	137	212
Storage Cost	£ ha^{-1} $harvest^{-1}$	22	40

From the data in Table 2-1 and a 6% discount rate, equation (2-1) can be represented as equations:

$$AEV_{scr} = 0.857\, p_{src}\, y_{src} - 248 \qquad (2\text{-}2)$$

$$AEV_{misc} = 0.907\, p_{misc}\, y_{misc} - 409 \qquad (2\text{-}3)$$

where: p_{src} and p_{misc} are the prices and y_{src} and y_{misc} are the yields for SRC and Miscanthus respectively. The AEV can be seen to have a linear relationship to the associated energy crop income. The slope is determined by the discount rate based on the harvest schedule. The costs and discount rate determine the constant. From this representation it can be clearly seen that SRC has lower costs overall. Also that the gross margin increases more slowly for SRC for a given increase in income.

The cause is mainly the reduced yield in the first SRC harvest, plus the 3-year harvest cycle delaying the income received in comparison to Miscanthus. The additional lifespan is only partially able to offset these differences. Finally, the equivalence of the impact of changes in price and yield on AEV can be noted.

Aylott *et al.* (2010) quoted the mean SRC yield for available areas in England of 9.7 (oven dry tonnes) odt ha^{-1} year^{-1}. The average yield for Miscanthus, derived from 14 arable site data in the UK, was 12.8 odt ha^{-1} year^{-1} (Richter *et al.*, 2008). Estimated for Miscanthus was £60 odt^{-1} (NNFCC, 2010a; Sherrington & Moran, 2010). Some studies have taken as £40 odt^{-1} for SRC (Aylott *et al.*, 2010; Sherrington & Moran, 2010), however the higher figure of £50 odt^{-1} from (NNFCC, 2010b) has been used. As will be shown, in most cases the results were that the energy crops were not selected within the optimal farm plan. Therefore, for sensitivity analysis a higher figure of 16 odt ha^{-1} year^{-1} for both crops was taken as the base line case. For SRC the yield is 0.5 odt ha^{-1} year^{-1} higher than the highest yielding sites (Aylott *et al.*, 2010). For Miscanthus it represents a more plausible case, within the observed range of site yields, although at the higher end (Richter *et al.*, 2008). Table 2-2 summaries these figures.

Table 2-2: Estimates and sensitivity ranges for energy crop rates.

Parameter	Unit	Estimated	Sensitivity base	Sensitivity range
SRC Price	£ odt^{-1}	50	50	40 to 100
Miscanthus Price	£ odt^{-1}	60	60	40 to 100
SRC Yield	odt ha^{-1} $year^{-1}$	9.7	16	5 to 18
Miscanthus Yield	odt ha^{-1} $year^{-1}$	12.8	16	5 to 20
Discount Rate	%	6	6	2 to 12
Grant Rate	%	50	50	0 to 100

Table 2-3 shows the conventional crop gross margin, with all work charged at contract rates. The nitrogen application rate producing the highest margin is shown in each case. The comparative AEV for the energy crops are also shown, calculated using the estimated and scenario base line values from Table 2-2. With a profit maximising LP model the figures suggest the solution is likely to be dominated by wheat and potatoes, in a ratio governed by the rotational constraints. However by including a representation of risk more diverse behaviours are possible.

Table 2-3: Margins by crop, using estimated values for energy crop data.

Crop	**Margin (£ ha^{-1} year^{-1})**
Winter Wheat	447
Winter Barley	288
Spring Barley	136
Winter Oats	425
Oilseed Rape	491
Sugar beet	1260
Field Peas	153
Field Beans	378
Ware Potatoes	1643
SRC – Estimated values	167
Miscanthus – Estimated values	288
SRC – Scenario baseline	438
Miscanthus – Scenario baseline	462

2.3.4 Risk model

Markowitz (1952) and Freund (1956) originally proposed a portfolio choice approach using expected return-variance of return (E-V) decision rule. Both this and an expected income-standard deviation (E-σ) approach have been used in farm-scale models (Hazell & Norton, 1986). The standard deviation implementation can be expressed as:

$$maximise\ U = E - \varphi\sigma \tag{2-4}$$

where: U is the utility; E is the expected income; φ, the risk-aversion parameter, assuming constant absolute risk-aversion; and σ is the standard deviation.

This standard deviation approach was selected for this application. The approach was chosen for a number of reasons. Firstly, the risk figure does not dominate the utility function as quickly as with the variance approach (E-V). Secondly, and perhaps most usefully, the risk-aversion parameter is unit-less and comparable to other studies (Hazell & Norton, 1986). Norgaard & Killeen (1980) showed the approach represents an exponential utility function and a truncated normal income distribution. That is, the tails of the distribution do not reflect reality in the eyes of the decision-maker. A value of zero implies no risk-aversion and therefore the same behaviour predicted by a profit maximising LP model would be expected.

The total standard deviation for a set of activities was determined through the use of a pre-calculated matrix of variances and covariances. This was used to calculate the total variance, or σ^2. The total standard deviation can be represented as:

$$\sigma = \sqrt{\sum_{i}^{n}\sum_{j}^{n} x_i x_i \sigma_{ij}} \qquad (2\text{-}5)$$

where: x_i is the activity level for the i^{th} activity and σ_{ij} is the co-variance of gross margin between the i^{th} and j^{th} activities of n activities, if i=j σ_{ij} is the variance of the i^{th} activity. The resultant mathematical programme is therefore non-linear. The model was a relaxed mixed integer non-linear programme (RMINLP). The CONOPT3 solver within GAMS was used to optimise the model (Brooke *et al.*, 2010).

A risk-aversion parameter figure is needed for each model optimisation. Values were selected in line with the results of previous studies imputing the risk-aversion parameters. A central estimate of 1.0 was chosen, and the behaviour over the range 0.0 to 3.0 was investigated. Hazell and Norton (1986) cited various researchers imputing risk-aversions in the range of 0.5 to 1.5. Although some studies have found or assumed values slightly outside this range, for example Semaan, et al. (2007) used 1.65; and Brink & McCarl (1978) imputed 0.23. Within a group of farmers a range of preferences, including for risk-aversion, is likely to occur (Rounsevell *et al.*, 2003).

2.3.5 Variance and covariance matrix

A matrix of variance and covariance was used to encapsulate the associated levels of uncertainty and correlations between activities, calculated from historical data. Each variance and covariance calculations applied the Bessel's correction to give an unbiased estimate, assuming the observations are from a sample of a normal distribution (Weisstein, 2011). The matrix was calculated prior to the model optimisations, and used in each model optimisation with the same set of historical data. As a result the total computational time is reduced where a large number of optimisations are required.

The objective is to represent some of the key factors and processes involved, although perhaps unconsciously, in the farmer decision-making. Therefore an estimate of uncertainty needs to be derived over a timeframe likely to be recalled by the farmer in their estimation of risk. The 20-year period from 1990 to 2009 was chosen.

2.3.5.1 Uncertainty of income

The variance and covariance matrix was calculated in income terms. It was assumed that the uncertainties of input costs were relatively small and were not included. An income for each year and crop in the historical dataset was determined prior to imputing the covariances.

DEFRA data were used for all conventional crop historical data (DEFRA, 2010). This will be likely to under-estimate the variances, as the data are already an average across the country for each year. This is especially true in the case of the yields, where variations experienced by individual farm will be averaged out (Freund, 1956). However insufficient data were available to use a disaggregated set of values.

2.3.5.2 Energy crops variance and covariance

There are numerous sources of risk, which will be subjective, and so vary between farm decision-makers. Sources of uncertainties can be categorised as impacting prices, costs or yields. As novel crops, farmers will be unfamiliar with the management of energy crops, potentially leading to the perception of increased yield uncertainty. Costs are perhaps the least significant element of risks in comparisons. The majority of the costs occur at establishment and these should be able to be determined with some certainty. It is likely that the price of the crop will be another significant source of uncertainty, and again the farmer initially has no direct experience to draw upon.

No suitable direct historical data series was available to determine an estimate of the uncertainty in the energy crop price, so a suitable alternative was required that was well correlated to them. Energy crop prices are believed to be strongly correlated to the oil markets (Song *et al.*, 2010). Both provide a source of energy, and to a limited extent could be considered as substitutes. Therefore fuel oil price data were chosen to generate an energy crop price variance index (DEFRA, 2010). These data were indexed using the most recent value to determine indexed variances and covariances to the other activities, with the result used as the indexed energy crop price variances and covariances.

An estimate of yield uncertainty was also generated. The standard deviation of yields in field trials for Miscanthus was measured as 2.9 odt ha^{-1} $year^{-1}$ at a mean of 12.8 odt ha^{-1} $year^{-1}$ (Richter *et al.*, 2008). This figure was used to determine a indexed yield variance for both SRC and Miscanthus. An alternative approach was also tried, using the yield variance in the conventional crop data. Choosing the conventional crop with the highest variance, linseed, and rebasing it based on mean yields resulted in an estimate of a standard deviation of 2.7 odt ha^{-1} $year^{-1}$. The two approaches produced similar results suggesting that farmers' perception of yield variability may be similar if they base it on crop trial data or their own experiences of other crops. The higher estimate from crop trial data was used within the model.

The price and yield components needed to be combined to give an overall value for the income variance. It was assumed that the price and yield index variation for energy crops were uncorrelated. The variance of products of two independent variables can be give as:

$$\sigma_{ab}^2 = \sigma_a^2\sigma_b^2 + \bar{a}^2\sigma_b^2 + \bar{b}^2\sigma_a^2 \qquad (2\text{-}6)$$

where: $\bar{a}$ and $\bar{b}$ are the means of the respective variables a and b (Barnett, 1955). This approach was used to combine the variances of price and yield and provide an estimate of the indexed energy crop income variance.

The variance and covariance indexes derived were rebased using the expected income of the energy crop. The income was derived from the yield and price expectation for each scenario being optimised. As a result the level of energy crop income risk was dependent on the expected income, with higher expected incomes giving rise to higher risk levels.

The energy crop income variance calculations have used some significant assumptions. Decision-makers may choose to be more conservative with respect to their assessment of energy crop uncertainty. To represent this a factor was applied to the energy crop variance. This factor can be considered to represent the additional risk or the perception of it. A factor of 1.5 was chosen as the central figure, implying approximately a 22% increase in the resultant energy crop standard deviation. It is believed that farmers' risk-aversions are typically within the range 0.5 to 1.5 (Hazell & Norton, 1986). Nevertheless, to examine the response a wider range of risk-aversions, from 0 to 2.0, was used. The parameters associated with the risk representation are collated in Table 2-4.

Table 2-4: Risk parameters estimates and ranges used for sensitivity analysis.

Parameter	Estimate & scenario base	Scenario range
Risk-aversion (φ)	1.0	0 to 2.0
Energy crop variance factor	1.5	0.5 to 3.0

2.4 Results

2.4.1 Correlation of incomes from energy and conventional crops

The resultant matrix of covariance and variance are shown in Table 2-5, using the estimated values from Table 2-2 and Table 2-4, duplicate values are excluded for clarity. This demonstrates that energy crop incomes have low or negative correlations with incomes from all conventional crops, given the assumption of energy crops prices correlating with the oil market.

Table 2-5: Table of crop income variance and covariance (1000 £^{2} ha^{-2}).

	Wheat	Barley	Oats	OSR	Sugar beet	Peas	Beans	Potatoes	SRC	Miscanthus
Wheat	61									
Barley	46	37								
Oats	42	33	31							
OSR	46	32	31	54						
Sugar beet	60	45	42	52	117					
Peas	48	40	34	25	49	54				
Beans	37	31	26	19	36	41	36			
Potatoes	57	42	19	-4	-38	24	-13	1744		
SRC	-6	-6	-5	-11	-22	-3	-1	42	42	
Miscanthus	-9	-9	-8	-18	-35	-5	-2	66	49	105

2.4.2 Farm models conventional crop response

The response of the model without energy crops was determined for a range of risk-aversions. Figure 2-1 shows the results for all crops selected by the model. With low risk-aversion the model behaves as expected for a profit maximising LP model with the highest margin crops selected, constrained by rotational constraints. However as risk-aversion increases the standard deviation term of the utility function starts to have more impact. The crop plans selected are those that lower risk, with winter oats as the cereal crop, with a mixture of sugar beet and ware potatoes as the rotation. Between the two levels of risk-aversion there is a mixture of behaviour. At even higher risk-aversions beans and OSR are selected. After risk-aversion of 7, beans come into the plan, eventually approaching a plan with only oats and beans as the risk term entirely dominates. In the range 11 to 16, there is a small area (up to 1.3%) of OSR selected.

Hazell and Norton (1986) cited various researchers imputing values in the range from 0.5 to 1.5. There will be variation in farmers' personal views leading to a more diverse set of responses then at any single risk-aversion value (Rounsevell *et al.*, 2003).

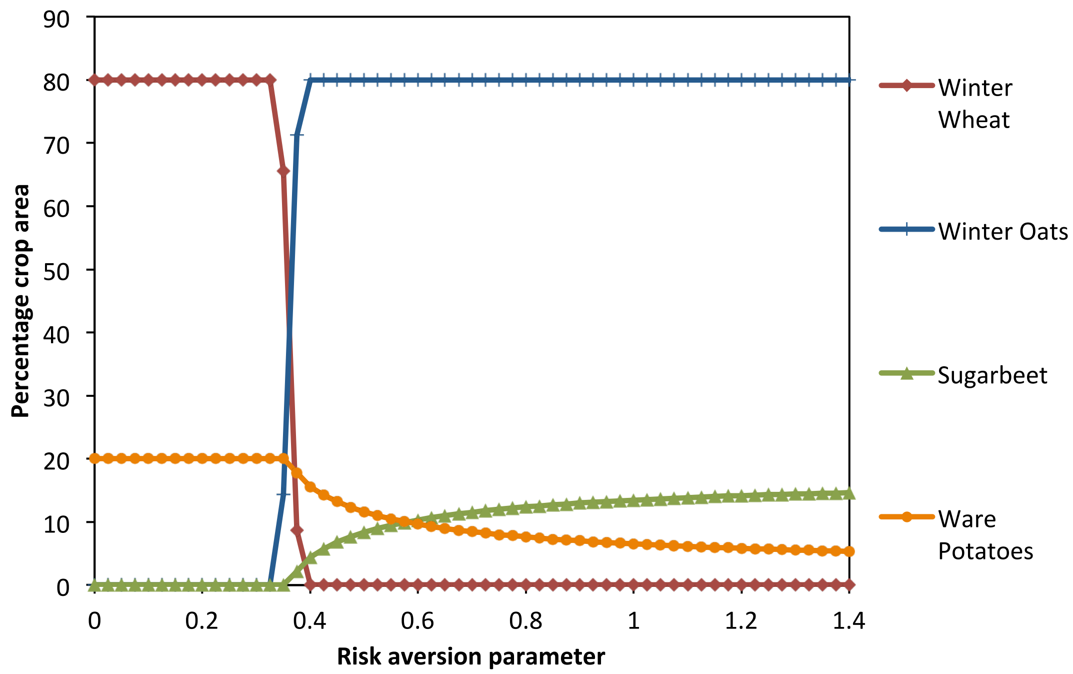


Figure 2-1: Conventional crop areas selected versus risk-aversion parameters.

2.4.3 Model validation

Due to lack of sufficient observed energy crop data, validation to observed data was only attempted for conventional crops. The DEFRA agricultural 2009 arable crop data were used (DEFRA, 2010), as shown in Table 2-6.

Table 2-6: Percentage cropping areas England & Wales.

Crop	Observed	Predicted
Cereals	69	80
Wheat	*40*	*80 to 0*
Barley	*26*	*0*
Oats	*3*	*0 to 80*
Oilseeds	13	0
Potatoes	3	20 to 5
Sugar beet	3	0 to 15
Peas and beans	5	0
Other	7	0

Using the individual cereal crops, the lowest net difference occurs at a 0.35 risk-aversion. Looking at aggregated cereals, the best fit occurs at risk-aversions above 0.4, due to the predictions of lower potato area and higher sugar beet. However there are some significant differences. The model never selects oilseeds in the expected risk-aversion range, as they are effectively competing in the rotation with the higher expected margins from potatoes and sugar beet. Also, the allocation of cereals does not fit with observations. The model is significantly over-predicting oats, and under-predicting barley at risk-aversion higher than 0.4. This is being driven by the relatively low variance calculated for oats, and the relatively low return on barley. A risk-aversion of 0.35 is within the range previously used or imputed for other farm models using this representation of risk (Brink & McCarl, 1978; Hazell & Norton, 1986; Semaan *et al.*, 2007). Although there is room for improvement, the current lack of spatial specificity and the intended use, the level of fit was deemed acceptable.

2.4.4 Energy crop response

The Miscanthus response over a range of risk-aversions and prices were determined using the estimated values, the results are shown in Figure 2-2. The inclusion of risk-aversion brings the Miscanthus into the optimal crop selection at a lower price, even when lower gross margins are expected, due to the reduced risk of a diversified crop selection. The reduction in risk-arises as the income from conventional crops and energy crops are not well correlated; for some conventional crops the correlation to energy crop income is marginally negative (see Table 2-5). The greater the risk-aversion the lower the Miscanthus price before any Miscanthus is selected. The higher the risk-aversion parameter, the greater the role of the risk terms in the overall utility function (see Equation 2-4). As the risk term becomes more dominant, the benefit of diversification from the conventional crops becomes sufficient to overcome a greater reduction in margins.

At £100 odt^{-1} Miscanthus has become the crop with the highest margin. In the case where the risk-aversion parameter is zero, the objective function is purely to maximise gross margin. Therefore the crop is selected for 100% of the area, as there are no rotational or other constraints to restrict it. At a lower price, there is no selection, as it is not the highest gross margin crop. The greater the risk-aversion parameter the more significant the risk term becomes, until at the highest risk-aversions parameters the term dominates the overall utility. The result is that, for all Miscanthus prices, the gross margin component responses converge to a similar point, around 19%, at high risk-aversions. They do not converge to the same point, as the variance for the energy crops is a function of the crops expected income. At risk aversions typically expected (0.5 to 1.5) neither the expected return nor risk terms entirely dominate. Using the estimated risk-aversion of 1.0, Miscanthus is not selected until £70 odt^{-1}, at 4% of the area, increasing to 13% at £80 odt^{-1}.

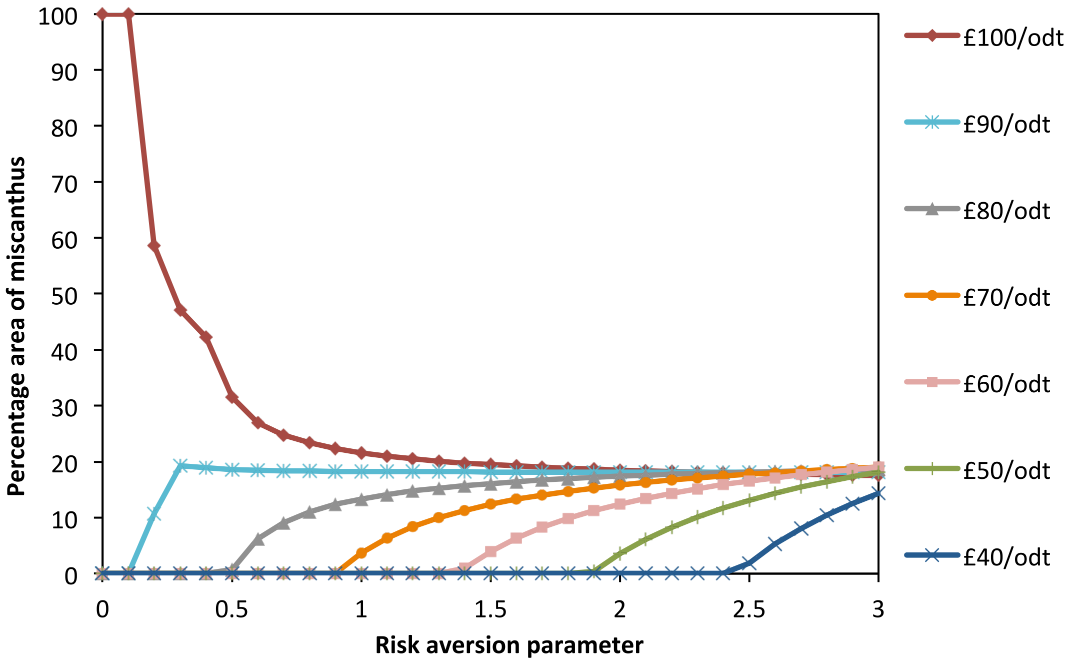


Figure 2-2: Miscanthus area at yield of 12.8 odt ha^{-1} by risk-aversion for a range of Miscanthus prices.

Income against the standard deviation of income for a range of risk parameters is shown in Figure 2-3. The result produces an efficient frontier, i.e. those plans that provide the least variance for a given level of expected income (McCarl & Spreen, 1996). As risk-aversion increases the level of uncertainty of income decreases, but to achieve this the expected income reduces. The rate of the reduction in expected income increases as the required certainty of income increases. The increasing price leads to greater income for a given level of uncertainty. As more Miscanthus comes into the plan, and at higher margins, the greater the shift.

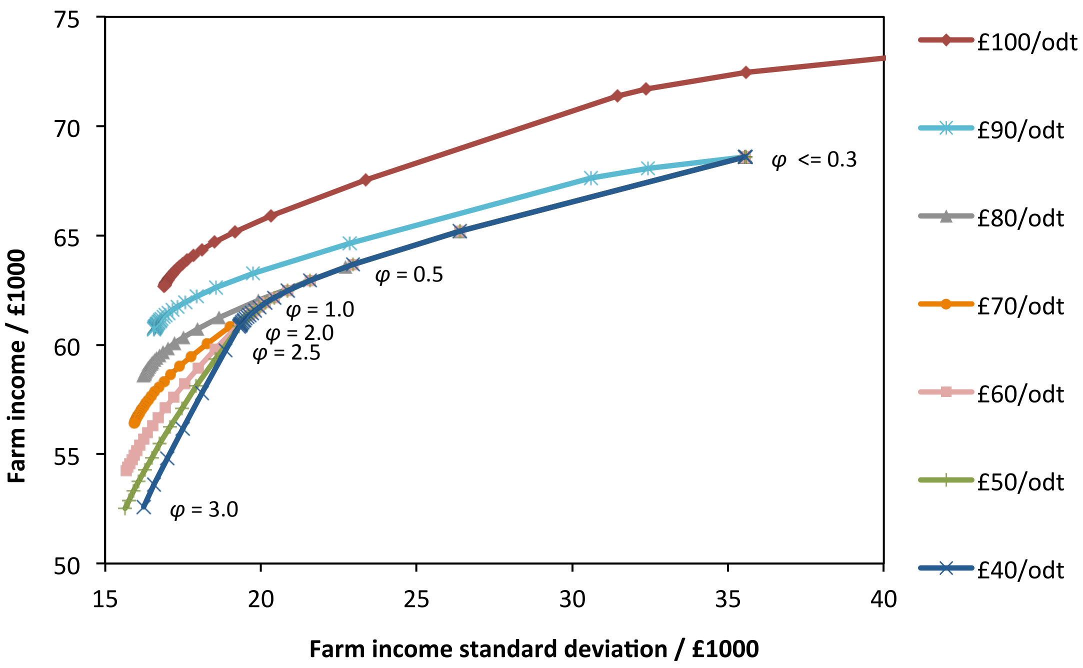


Figure 2-3: Farm income versus standard deviation of income for a range of Miscanthus prices at Miscanthus yield of 12.8 odt ha^{-1}.

Optimising both energy crops together using the estimated values, produced no SRC response. To investigate the SRC behaviour the Miscanthus activity was suppressed. Figure 2-4 shows the level of SRC selected for a range of prices and risk-aversion parameters. Taking the estimated figures, SRC was not selected until £80 odt^{-1}at a rate of 6%.

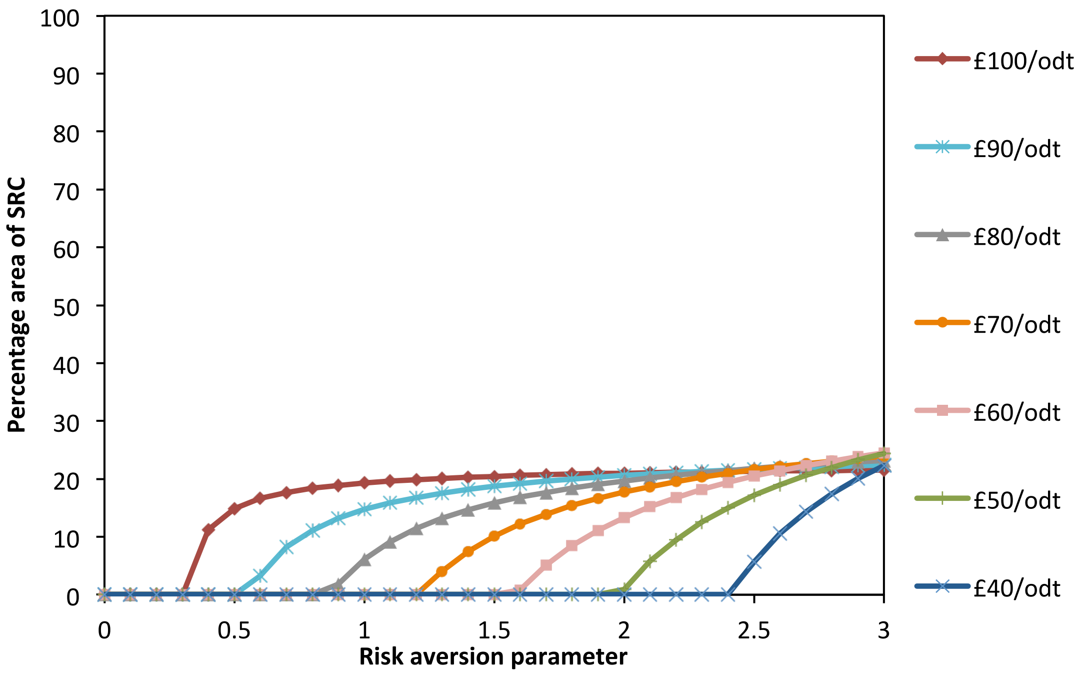


Figure 2-4: SRC area at yield of 9.7 odt ha^{-1} year^{-1} by risk-aversion for a range of SRC prices.

Sensitivity analysis was conducted for each energy crop, and used to produce 'spider diagrams' (Pannell, 1997). Sensitivities for Miscanthus are shown in Figure 2-5. The equivalent sensitivity analysis was conducted for SRC, showing similar behaviour. Noted differences included SRC having a higher sensitivity to the discount rate and risk-aversion.

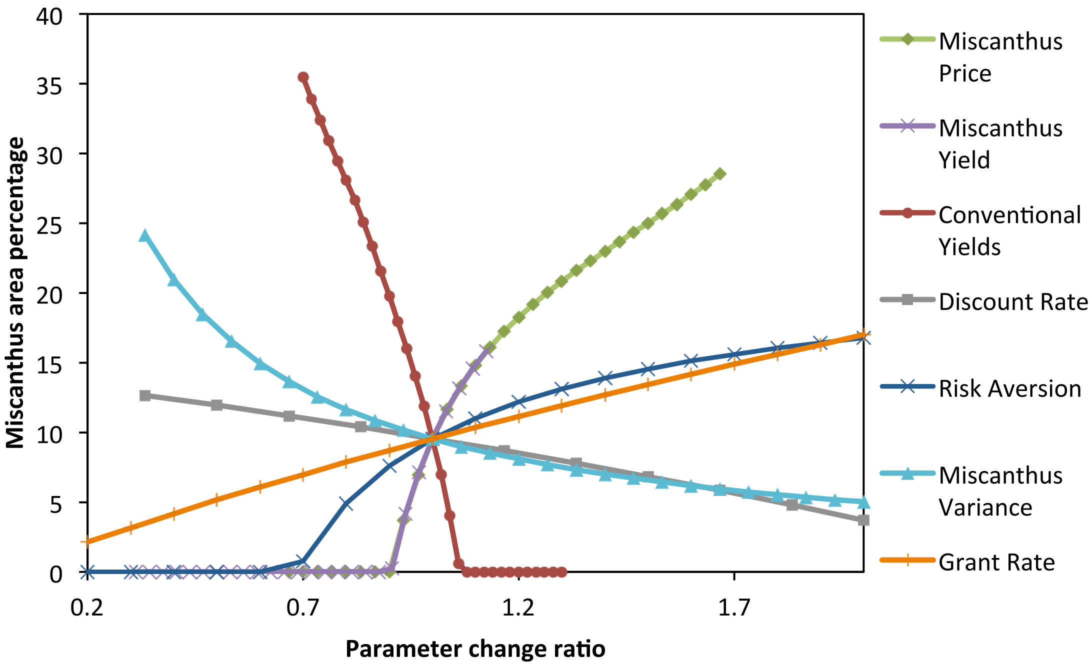


Figure 2-5: Model parameter sensitivities for Miscanthus, showing percentage Miscanthus area selected against ratio change for each parameter.

High sensitivity to variations in the yields of conventional crops was displayed. An 6% increase in conventional crop yields was sufficient to remove the Miscanthus area selected, even at this high estimate of Miscanthus yield (16 odt ha^{-1} year $^{-1}$ compared to a estimated average in the UK of 12.8 odt ha^{-1} year $^{-1}$). While a 10% decrease saw a doubling of Miscanthus selection to 20%. The sensitivity to changes in Miscanthus price or yield was also high. Both take identical forms, as both energy crop AEV and variance are functions of the base income.

The selected area displayed a relatively low sensitivity to the rate of establishment grant in comparison to other model parameters. The AEV approach spreads the initial costs over the lifespan of these crops, so large changes in establishment grant rates (or establishment costs) are required to significantly change the annualised gross margin and therefore the crop selection. Using the UK mean estimated energy crop yields the model was used to find the grant rate required to generate the first energy crop selection. The results were 106% and 350% of establishment costs for Miscanthus and SRC respectively.

2.5 Discussion

The covariances produced (see Table 2-5) show that the energy crop incomes are not strongly correlated to the incomes of conventional crops, for most conventional crops the correlation is negative. This implies that portfolio of crops containing conventional and energy crops could provide a more stable income, with a lower income variance. Therefore if the farmer's utility function includes an aversion to risk the lowered risk of such a portfolio provides an incentive for diversification into energy crops.

The farm model implemented demonstrates such behaviour where increased risk-aversion results in greater likelihood of energy crop selection. This appears contrary to previous work asserting risk is seen as a barrier to uptake of energy crops (Styles *et al.*, 2008; Sherrington & Moran, 2010). However the result is for a fixed estimate of uncertainty for all activities, including the energy crops. If a farmer is to be modelled as having a particularly high level of perceived uncertainty relating to energy crops then the model's income variances associated with these crops, rather than the farmers overall risk-aversion, should be adjusted to represent that view. Sensitivity analysis showed that the area is reduced when uncertainty relating to energy crop income is increased (see Figure 2-5).

Annualising the returns from the perennial energy crops, to allow comparison with conventional arable crops, excludes some aspects that may be important to farmers' decision to adopt these crops. Perhaps most significantly, it does not take account of the irreversibility, due to the costs associated with establishing and removing these energy crops (Table 2-1). The farmer has the option (i.e. the right, but not the obligation) to convert conventional arable crops into energy crops when they consider the market conditions are suitable, but it is costly to revert after this decision has been made. An additional value, termed the real option value, derives from this ability to select when and if to convert (Dixit & Pindyck, 1994). Analysis of the impact of real option value on perennial energy crop selection suggests that higher costs of conversion lead to a potential delay in the adoption of energy crops (Song *et al.*, 2010). However, it is also associated with a resistance to change back to conventional crops (Song *et al.*, 2010). The model presented here does not account for the value of this option, and as a result may somewhat overstate the adoption rate. The energy crop variance factor, used to increase farmers' perception of the risk associated with energy crops, should act to offset this bias. A real option value analysis was considered out of scope for this work due to the considerable complexity involved.

The results suggest that only a small area of Miscanthus would be expected to be established in the highest yielding sites and that SRC would be even more marginal. Given average yields, energy crops were only selected when the farm gate price were £80 odt^{-1} and £70 odt^{-1} for SRC and Miscanthus respectively, using the estimated figures, Table 2-2 and Table 2-4. This is significantly higher than the estimated market prices, at 60% increase for SRC and 17% for Miscanthus. As highlighted the price or yield variations are equivalent. Therefore this can be restated as a minimum yield of 15.5 odt ha^{-1} $year^{-1}$, and 14.9 odt ha^{-1} $year^{-1}$, given current price estimates. The required SRC yield is equal to the highest estimated site yield predictions, and substantially more than the highest yield regional mean at 10.9 odt ha^{-1} $year^{-1}$ (Aylott *et al.*, 2010). The required Miscanthus yield is lower than the maximum 18 odt ha^{-1} $year^{-1}$ observed but significantly more than the 12.8 odt ha^{-1} $year^{-1}$ UK mean (Richter *et al.*, 2008). Even at these levels, areas selected for each energy crops were small, 6% for SRC and 4% for Miscanthus. This suggests that the level of planting of energy crops in 2009 would have been expected to be low.

The sensitivity analysis showed there are a number of factors affecting energy crop selections. High levels of sensitivity to yields of conventional crops and energy crops were noted. The same rates of sensitivity were also displayed to energy crop prices. Lower rates of sensitivity were seen for the parameters related to the risk representation. However it is arguable that these figures have a higher degree of variability associated with them. The sensitivity to establishment grant rates was found to be low, and more than 100% grant rates required to make energy crop selection optimal, in the case of SRC significantly more (3.5 times). The costs and subsidies that occur at establishment are considered to be spread over the productive lifespan of the plantations. If a low gross margin crop is to be grown for a long period, 21 years in the case of SRC, then the opportunity cost is substantial.

Many of the model parameters vary by location or time, and others are dependent on farmers' perceptions. Therefore, a more variable response than any single set of parameters suggest would be expected. A disaggregated approach is needed to represent some of this complexity, for example to include the spatial variability of conventional crops and energy crops. For example, if relatively higher energy crop yields can be obtained on land that produces relatively poor yield for conventional crops then the threshold for selecting the energy crop would be reduced. The level of sensitivity to each parameter suggests that even small differential variations in yields could have a significant impact to the optimum crop selection. Such an analysis was conducted across the UK, is presented in Chapter Three, to provide an improved estimate of the potential total area and biomass resource for each crop.

2.6 Conclusions

Historical data suggests that income from energy crops will not be well correlated to conventional crop incomes. This could possibly provide an incentive for risk-averse farmers to establish these crops. However the farm-scale model implemented suggests that even given this effect Miscanthus would be optimal only on the highest yielding sites, above 14.9 odt ha^{-1}, given estimated values and a price of £60 odt^{-1}. SRC may not be an optimal choice on any UK site at a price of £50 odt^{-1}, requiring a yield of at least 15.5 odt ha^{-1}. Large increases in establishment grant rates, to over 100%, are required to substantially alter the indicated crop selections. However these conclusions must be regarded as tentative due to a number of parameter assumptions. Sensitivity analysis showed that the energy crop selection had particularly high sensitivity to the yields of both conventional and energy crops. Therefore to reach a more definitive conclusion on the levels of economic growth requires work to include the spatial variability of these yields.

Chapter three presents further work conducted to incorporate the use of spatially disaggregated data for the UK, the output of which includes maps of economic energy crop growth and an improved estimate of the overall supply of these perennial energy crops in the UK.

CHAPTER THREE

SUPPLY ESTIMATES USING FARM-SCALE MODELS WITH SPATIAL DATA

After article: Alexander P, Moran D, Smith P, *et al.* (2014a) Estimating UK perennial energy crop supply using farm scale models with spatially disaggregated data. *Global Change Biology Bioenergy*, 6, 142-155. See Appendix II.

3.1 Abstract

To achieve the UK Government's aim of expansion in the growth of perennial energy crops requires that farmers select these crops in preference to conventional rotations. Existing studies estimating the total potential resource have either only simplistically considered the farmer decision-making and opportunity costs, for example using an estimate of annual land rental charge; or have not considered spatial variability, for example using representative farm types. This chapter attempts to apply a farm-scale modelling approach with spatially specific data to improve understanding of potential perennial energy crop supply. The model's main inputs are yield maps for the perennial energy crops, Miscanthus and willow grown as SRC, and regional yields for conventional crops. These are used to configure location specific farm-scale models, which optimise for profit maximisation with risk-aversion. Areas that are unsuitable or unavailable for energy crops, due to environmental or social factors, are constrained from selection. The results are maps of economic supply, assuming a homogenous farm-gate price, allowing supply cost curves for the UK market to be derived. The results show a high degree of regional variation in supply, with different patterns for each energy crop. Using estimates of yields under climate change scenarios suggests that Miscanthus supply may increase under future climates while the opposite effect is suggested for SRC willow. The results suggest that SRC willow is only likely to able to supply a small proportion of the anticipated perennial energy crop target, without increases in market price. Miscanthus appears to have greater scope for supply, and its dominance may be amplified over time by the effects of climate change. Finally, the relationship to the demand side of the market is discussed. The need for the work presented in Chapter Four is presented, to investigate the factors impacting how the market as a whole may develop.

3.2 Introduction

Increased biomass use is expected to contribute to the UK's target to source 15% of energy from renewable sources by 2020 (DECC, 2009). The UK Biomass Strategy identifies the prospect of part of the required supply coming from a major expansion in UK production of perennial energy crops, potentially using 350 kha, an area equivalent to 6.5% of total arable land (DEFRA, 2007). Despite the existence of financial incentives, the area of UK perennial energy crops established has so far been comparatively limited, at around 17 kha (RELU, 2009). The low level of uptake is supported by data from Natural England on the areas receiving establishment grants; in the period 2000-6 a combined area of 8191 ha was given grant support, while in the period 2007-11 the area was only 1305 ha (Natural_England, 2006, 2011).

A number of studies have investigated and modelled the biophysical properties of perennial biomass crops, as well as assessing the optimal spatial locations for production given biophysical constraints (Price *et al.*, 2004; Andersen *et al.*, 2005; Aylott *et al.*, 2008; Richter *et al.*, 2008; Hastings *et al.*, 2009), with other work applying environmental and socials constraints (Lovett *et al.*, 2009; Aylott *et al.*, 2010). The supply side economics of energy crops has been considered using a variety of approaches, perhaps the simplest is accounting for the opportunity costs using an estimate of annual land rental (Monti *et al.*, 2007; E4tech, 2009; Bauen *et al.*, 2010). Another commonly taken approach is to compare annual gross margins of conventional crops with an equivalent annualised value for the perennial energy crops (Bell *et al.*, 2007; Styles *et al.*, 2008; Turley & Liddle, 2008). Farm-scale economic models have also been used to investigate the potential uptake of perennial energy crops (Sherrington & Moran, 2010). Existing studies into assessing total potential perennial energy crop resource and supply curves appear either to have only simplistically considered the farmer decision-making and opportunity costs, for example using an estimate annual land rental charge; or have not considered spatial variability, for example using representative farm types (Sherrington & Moran, 2010). The importance of increased understanding in this area is apparent by looking at the low levels of uptake to date (RELU, 2009). To increase the understanding of the supply side of this market an improved estimate of the level of economic supply, how it is geographically distributed, and the supply response to changes in market price are required. This understanding could be used to investigate the potential impact of possible policies on the rate and level of development in the perennial energy crop market.

This chapter presents the use of a farm-scale modelling approach with spatially specific data to provide an improved understanding of the potential economic perennial energy crop supply from Miscanthus (*Miscanthus x giganteus*) and short-rotation coppice willow (genotype Joruun, *Salix viminalis* L. x *S. viminalis*). The farm-scale model construction and use is summarised, with the source of land use constraints and yield distribution data presented. The resultant maps of economic supply and supply cost curves for the UK market are given and discussed. The impacts of climate change scenarios on the results are also investigated.

3.3 Materials and methods

3.3.1 Overall approach

A farm-scale model was spatially configured for each location within the UK, using a $1km^2$ grid, representing a homogenous 100 ha farm size. The energy crop yields used were estimated at that spatial resolution (Tallis *et al.*, 2012; Hastings *et al.*, 2014), while the conventional crop yields were estimated from observed mean regional yield data. Areas where energy crops may not be appropriate for social or environmental reasons were excluded from selection (Lovett *et al.*, 2014), as described in the social and environmental constraints in this chapter. Areas where no demand was predicted for biomass from perennial energy crops (Wang *et al.*, 2014) were also excluded, as described in the demand constraints in this chapter. Once an optimised farm plan (i.e. based on constrained profit maximisation) is available for each location, the results can be extracted to produce maps of likely crop supply distribution, or data extracted to generate supply rates for different geographical areas. Running the analysis for a range of energy crop prices also allows supply curves to be generated, repeated using yields under UKCP09 climate change scenarios (Murphy *et al.*, 2009) to determine the response under these conditions.

Figure 3-1 gives details of the processes involved in spatially configuring the farm-scale model and extracting combined results from its multiple executions.

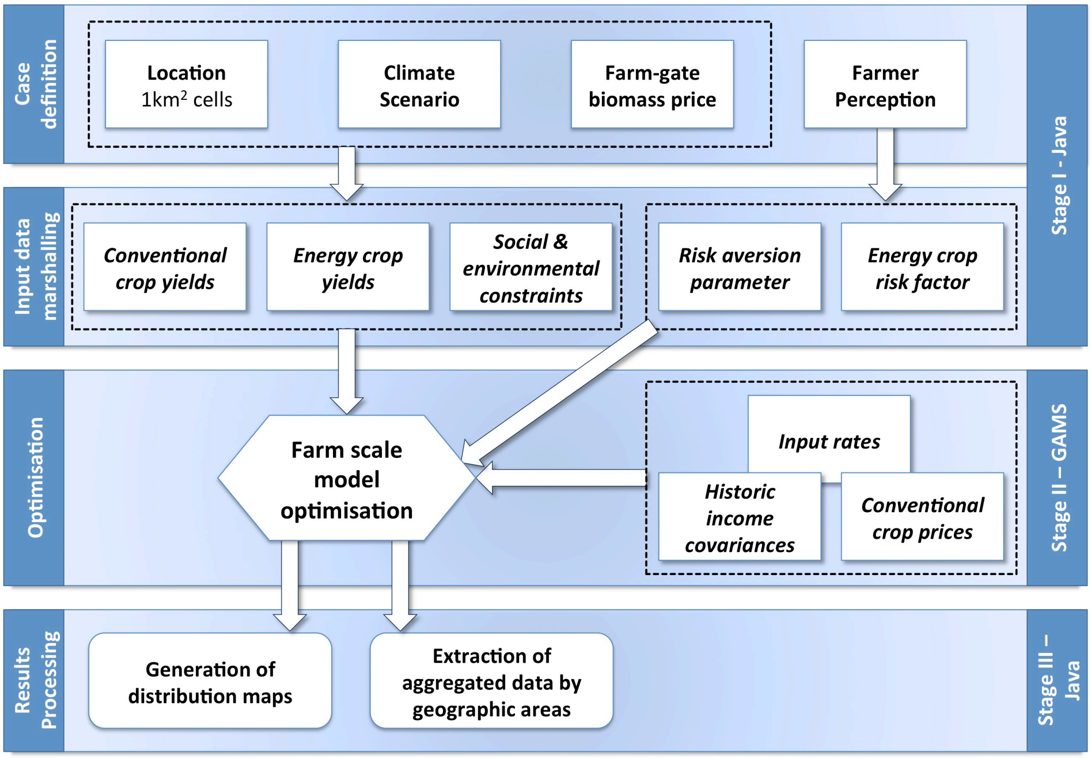


Figure 3-1: Flow diagram of process to configure and optimise farm-scale model to generate energy crop supply maps.

3.3.2 Farm-scale model

The farm-scale model represents decision-making in an arable farm type, where the optimisation criterion represents profit maximisation with constant absolute risk-aversion. It was initially developed to look at the impact of income variability and risk-aversion to the farmer selection of energy crops (Alexander & Moran, 2013). Conventional arable crop activities (winter wheat, winter barley, spring barley, winter oats, oilseed rape, sugar beet, peas, beans, and main crop ware potatoes), for multiple fertiliser application rates, plus the two energy crop activities were represented. Constraints were set on land availability and crop rotations. All operations are charged at contract rates, including an allocation for machinery cost and fuel cost. These rates are constant for all locations, any spatial variation in productions costs, e.g. due to soil types, are not represented. Prices, input rates and contractor rates were updated to use data from the SAC farm handbook 2010/11 (SAC, 2010). The resulting non-linear mathematical programme was implemented in GAMS and optimised using the CONOPT3 solver (Brooke *et al.*, 2010).

3.3.2.1 Energy crop representation

An annual equivalent value (AEV) approach was used to allow the comparison of the perennial energy crops with the annual gross margins of the conventional crops (Bell *et al.*, 2007; Sherrington & Moran, 2010). Future values were adjusted into 2010 terms using a 6% discount rate, representing an estimate of farmers' cost of capital (Sherrington & Moran, 2010). SRC willow plantations were expected to be harvested every 3 years (Armstrong, 1997). The total lifespan was taken as 21 years, or 7 harvests (Bauen *et al.*, 2010). Miscanthus plantations were harvested annually starting in the second year, with a 16 year lifespan (Styles *et al.*, 2008). For a given farm and scenario, the yields were assumed to be constant, with the exception of the first SRC harvest where the yield was reduced to 60% (Kopp, 2001). Prices are taken as farm gate prices, and assumed constant over the crop lifetime. A 50% establishment grant was included, as per with the Energy Crops Scheme (Natural_England, 2009). Fertiliser was taken as only being applied to SRC at planting and after each harvest (Bell *et al.*, 2007). Miscanthus does not require significant fertiliser application as it recycles nutrients, and was taken as 85 kg ha^{-1} nitrogen (N) and 45 kg ha^{-1} each of phosphorous (P) and potassium (K) at establishment, and 40 kg ha^{-1} of N assumed after year 5 and 10 (NNFCC, 2010a). Energy crop establishment figures and structure were followed from Bauen *et al.* (2010), adjusted to 2010 terms using the CPI inflation data (ONS, 2011), see Table 3-1.

Table 3-1: Rates for energy crops operations, 2010 £ terms based on Bauen *et al.* (2010).

Item	Unit	Miscanthus	SRC Willow
Establishment Cost	£ ha^{-1}	1949	2183
Establishment Grant	£ ha^{-1}	975	1092
Removal	£ ha^{-1}	109	547
Fixed overhead	£ ha^{-1} $year^{-1}$	95	95
Fertiliser	£ ha^{-1} $application^{-1}$	0	27
Harvesting Cost	£ ha^{-1} $harvest^{-1}$	219	141
Storage Cost	£ ha^{-1} $harvest^{-1}$	42	23

3.3.2.2 Risk model

The portfolio choice rule using expected income-standard deviation was selected in the farm-scale model applied, and can be expressed as:

$$maximise\ U = E - \varphi\sigma \tag{3-1}$$

where: U is the utility; E is the expected income; φ, the risk-aversion parameter, assuming constant absolute risk-aversion; and σ is the standard deviation. The reasons for selecting this approach are examined in Alexander & Moran (2013), including that the risk-aversion parameter is unit-less and comparable to other studies (Hazell & Norton, 1986). It is the key model parameter that cannot be directly set from observation or spatially specific data. As it represents a farmer's view on risk, a range of values would be expected within a set of farmers. Hazell & Norton (1986) cited various researchers imputing risk-aversions in the range of 0.5 to 1.5. In line with these results a central estimate of φ = 1.0 was chosen. Although some studies have found or assumed values slightly outside this range, for example Semaan et al. (2007) used 1.65; and Brink & McCarl (1978) imputed 0.23. To cover these cases, the behaviour of the model over the range φ = 0.0 to 2.0 was investigated.

3.3.2.3 Variance and covariance matrix

A matrix of variance and covariance was generated to encapsulate the associated levels of uncertainty and correlations between activities, and used to calculate the total income standard deviation for sets of activities. The variances and covariances were calculated from historical data over the period from 1990 to 2010, using DEFRA (2011a) data. Although this is likely to under-estimate the variance, as the data are already averages (Freund, 1956), insufficient data were available to use a disaggregated set of values. The variances and covariances were calculated in income terms, as it was assumed that the uncertainties of input costs were relatively small.

3.3.2.4 Energy crops variance and covariance

No suitable direct historical data series were available to determine an estimate of uncertainty in the energy crop price. Energy crop prices are believed to be strongly correlated to the oil markets (Song *et al.*, 2010), therefore fuel oil price data were chosen to generate an energy crop price variance index (DECC, 2010). An estimate of yield uncertainty was generated using the standard deviation of yields in field trials for Miscanthus (Richter *et al.*, 2008). The price and yield variances were combined to provide an estimate of the indexed energy crop income variance, assuming that they were uncorrelated (Barnett, 1955). The indexed variances and covariances were rebased using the expected energy crop income for each scenario being optimised. Decision-makers may choose to be more conservative with respect to their assessment of energy crop uncertainty. To represent this, a factor was applied to the energy crop variance. This factor can be considered to represent the additional risk or the perception of it. As per Alexander & Moran (2013) a factor of 1.5 was chosen as the central figure, implying approximately a 22% increase in the resultant energy crop standard deviation.

3.3.2.5 Farm-scale model validation

Validation was done to observed conventional crop data, due to lack of sufficient empirical data for energy crops with the lowest net difference occurring at a risk-aversion of $\varphi = 0.35$ (Alexander & Moran, 2013). This is within the range previously used or imputed for other farm models using this representation of risk (Brink & McCarl, 1978; Hazell & Norton, 1986; Semaan *et al.*, 2007) and within the range which behaviour was investigated. Alexander & Moran (2013) gives further details of the farm-scale model construction, validation, and sensitivity analysis.

3.3.3 Relative energy crop price

The low heating value (LHV) was used to provide a consistent price for biomass energy from each energy crop. LHV, also known as net calorific value, is the energy released on combustion after the water contained in the fuel has been vaporised. Miscanthus was assumed to have a moisture content of 15% and an LHV of 15.1GJ t^{-1}, while the SRC willow was taken as having 30% moisture, after a period of natural drying, with an LHV of 12.1 GJ t^{-1} (Hillier *et al.*, 2009). To allow comparisons or unbiased setting of the energy crops prices the LHV of each crop was used to convert between crop prices and biomass energy prices. The lower LHV value of SRC willow, due partially to higher moisture, implies a lower market price in comparison to Miscanthus. Taking a market price for Miscanthus of £60 odt^{-1} in 2010 terms (NNFCC, 2010a; Sherrington & Moran, 2010), the LHV figures imply an expected SRC willow price of £48 odt^{-1}. This figure falls in the range of previously estimated market prices for SRC willow, which was £40 odt^{-1} (Aylott *et al.*, 2010; Sherrington & Moran, 2010) to £50 odt^{-1} (NNFCC, 2010b). The remainder of the chapter will use £60 odt^{-1} and £48 odt^{-1} for Miscanthus and SRC willow respectively as estimates of current market prices. Where other prices are used, the relationship between the prices of these crops is maintained, such that, the price per net calorific energy is equal. All prices are in 2010 terms unless otherwise stated.

3.3.4 Spatial configuration

The farm-scale model behaviour displays highest sensitivity of energy crop area selected to the yields of conventional crops and energy crops (Alexander & Moran, 2013). Therefore, to generate an improved understanding of the potential economic supply of energy crops, variations in yields need to be included in the analysis. Crop yields will differ by site location, through variation in soil, climate and topography. Therefore a spatially disaggregated methodology is required to include yield variability. Such an approach allows the selection of energy crops to occur on sites where relatively low conventional crop yields are coupled with relatively high energy crop yields, contributing to more favourable expected energy crop returns. Distributions of yields across the UK for all the activities in the farm-scale model are needed to configure farm representations for each location. Constraint masks were required to limit the selection of sites to those likely to be deemed acceptable for energy crop growth from a social and environmental perspective, and to locations where demand for them could exist. A regular 1 km^2 grid was chosen, where each grid square was considered an independent 100 ha farm, and optimised as such. This resolution provides sufficient spatial detail to capture climate and large-scale soil variation, and was in line with the resolution of some of the yield inputs. It also provided a relatively realistic farm size, compared to the average UK farm size of 57 ha (UK Agriculture, 2013), and was computationally tractable.

Where required, the input data used were resampled to ensure a consistent coordinate system and grid size. More details on the data sources for each crop are given below. A Java programme was developed using the Java Development Kit 7 (Oracle, 2012) to read the various input distributions, collectively allowing the farm model input data for each location to be determined. Rather than directly optimising each case, only unique cases are optimised by identifying all cases that have duplicate input values. In this way the data for all locations with the same values can be handled by a single farm-scale model execution. Once the unique cases have been identified with the mapping from the location to the unique input data, the programme creates and executes the GAMS models for all the unique cases. The outputs of these optimisations are then associated with all the relevant locations to obtain a complete representation of all activities within the area studied. The data can then be output in various forms for further analysis.

The steps involved in the model execution can be seen in Figure 3-1, breaking each stage down further they can be summarised as follows:

Stage I – Input Marshalling

1. Reads all the input data, including yield data, scenario data, etc.
2. Determine the set of unique cases.
3. Create GAMS model for each unique case
4. Create mapping from raster cell to one of these model case.

Stage II – Optimisation

5. Executes each model in GAMS.

Stage III – Results Processing

6. Use farm-scale model outputs and the raster cell to model case data and creates output data files and images of the output data.

3.3.4.1 Conventional crop yield distributions

Although spatially disaggregated yield data for conventional crops would be highly desirable, no source of such data was available, so regional yields were used (DEFRA, 2011b; Scottish Government, 2011; Welsh Government, 2011). The data for Wales relates to 2009 while other data is for 2010. The regional yield data for England and Wales provided an aggregate figure for barley for each region, without the distinction between winter and spring sown crops. To provide a regional yield estimate, winter and spring barley figures were divided using the mean Scottish proportions, pro-rated to maintain the regional averages. No regional yield data was available for Scotland for sugar beet, peas or beans so the figures from North East England were used. Similarly, West Midlands figures were used for oilseed, sugar beet, peas or beans for Wales as these figures were not available in the Welsh Government dataset. To define the location of the regions, the OS boundary data was used (Ordnance Survey, 2011). The resultant yields maps for a sample of the key conventional crops are shown in Figure 3-2.

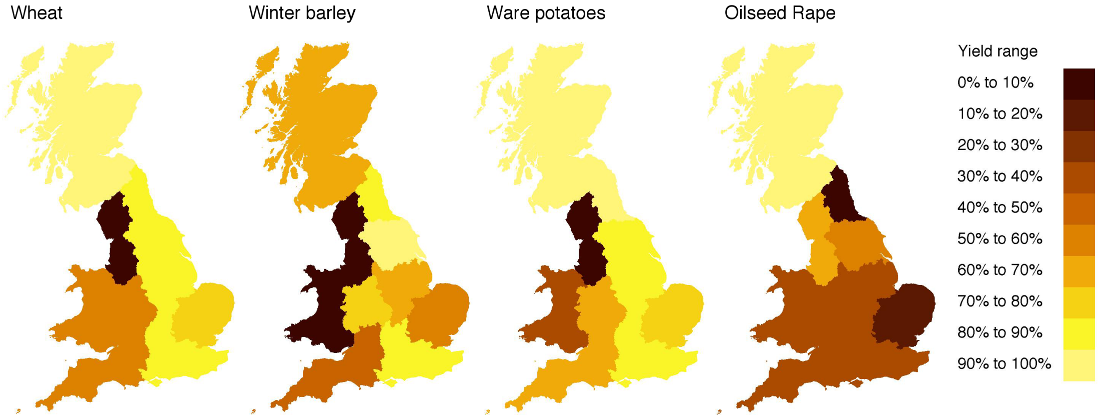


Figure 3-2: UK yield comparison maps of sample conventional crop, based on regional yield data for wheat, winter barley, ware potatoes and oilseed rape, showing variation between maximum and minimum yields for each crop. Data sources: DEFRA (2011b), Scottish Government (2011) and Welsh Government (2011).

3.3.4.2 Energy crop yield distributions

Miscanthus yield distributions were obtained from Hastings *et al.* (2014). These results were generated from the MISCANFOR model with UKCP09 climate data (Murphy *et al.*, 2009) and soils data from the harmonised world soil database (FAO/IIASA/ISRIC/ISSCAS/JRC, 2012) to estimate a peak yield over the UK using a 100m x 100m grid. Peak yield estimates were scaled by 0.67 to obtain harvestable yield after senescence and drying the following spring (Hastings *et al.*, 2014). The model was used to obtain yield estimates for each climate change UKCP09 scenarios. The resultant 100m x 100m raster data was resampled in ArcMap to a $1km^2$ grid coordinate system. SRC willow yield distributions were obtained from Tallis *et al.* (2012). To ensure consistency of results, the same soil and climate data were used. The SRC willow yield modelling was executed using a $1km^2$ grid over the range of climate change scenarios. The results for both the Miscanthus and SRC willow yield distributions for the 2010 climate baselines are shown in Figure 3-3. The changes to these yields under high emission climate scenarios for 2020, 2030 and 2050 are shown in Figure 3-4.

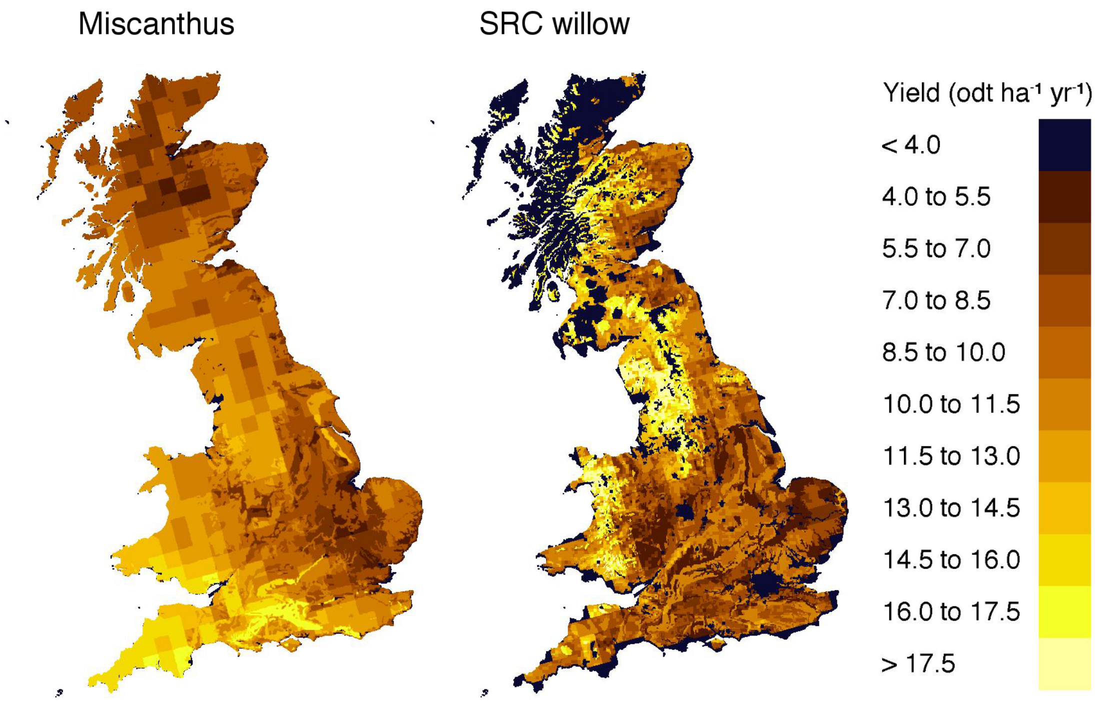


Figure 3-3: Unconstrained energy crop yield maps for baseline (2010) climate scenario for Miscanthus and SRC willow. Data source: Hastings *et al.* (2014).

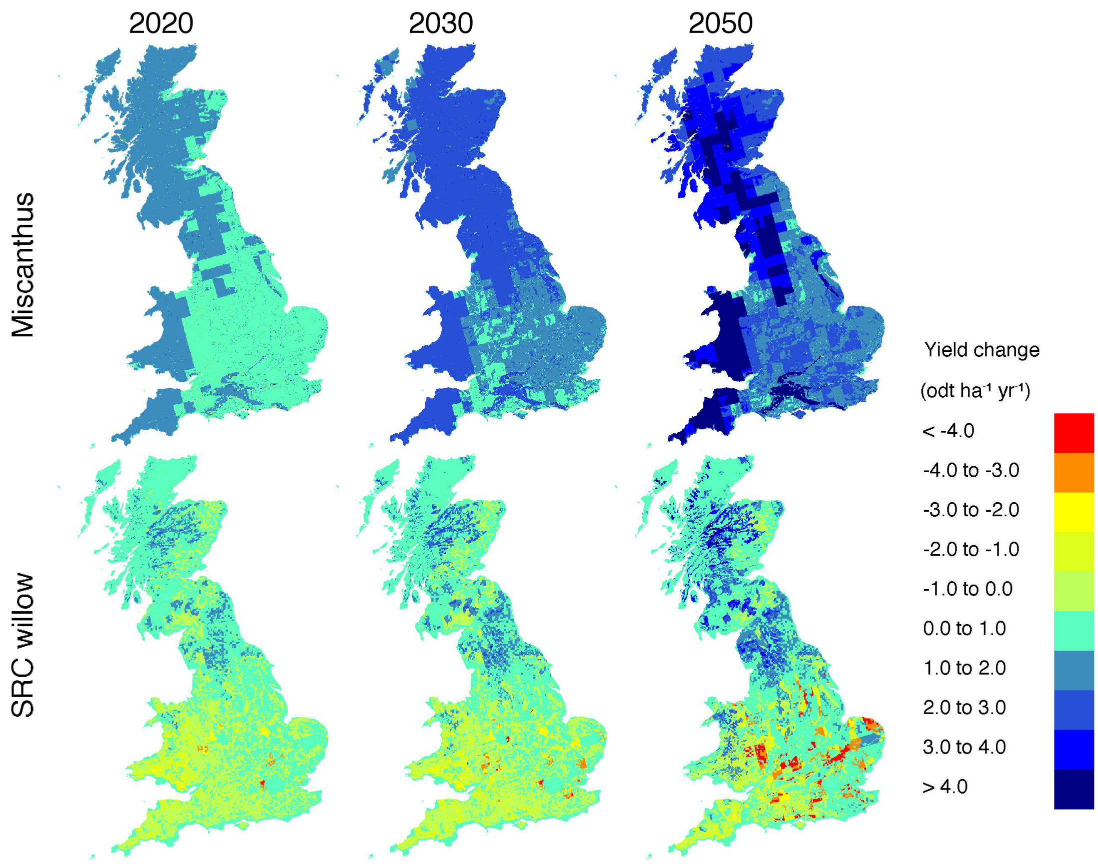


Figure 3-4: Miscanthus and SRC willow yield change maps from baseline (2010) climate scenario to 2020, 2030 or 2050 using high emission scenario. Data source: Hastings *et al.* (2014).

3.3.4.3 Constraints

Not all areas will be available for potential perennial energy crop growth, regardless of whether or not they may be economically grown at that location. Also as transportation costs are high due to the low energy density a local demand is needed. To exclude areas that would not be appropriate, two distinct types of land use restrictions were applied to constrain the selection; a set of social and environmental constraints, and a demand constraint.

i) Social and environmental constraints

Social and environmental constraints restrict the areas that would be available to grow these energy crops. Lovett *et al.* (2014) produced a mask of areas which would be unavailable based on 8 factors, these removed areas that were road, rivers and urban areas; slope > 15%; monuments; designated areas; existing woodlands; high organic carbon soils; and areas assessed has having a high ‘naturalness score’.

ii) Demand constraints

Wang et al. (2014) produced a distribution for the UK of economic energy crop demand given transportation costs to locations where heat and electricity demand may exist. The model is able to exogenously specify land competition percentage to constrain the area available for energy crops. The supply-demand model of Wang *et al.* (2014) provides estimates of where energy crops could provide cost-effective supply of heat and electricity, but does not consider farm-scale economics determining whether farmers will decide to plant energy crops rather than conventional crops. To achieve this, the farm-scale model described here is used, to represent competition for land, and to limit the area use for energy crops, by assuming that the farmers’ economics provides an appropriate mechanism for the efficient allocation of land resource. The areas found to be unsuitable for energy crop production to supply electricity and heat to areas of demand by Wang *et al.* (2014) were excluded. A map showing these two constraints can be seen in Figure 3-5. The areas available for potential selection of energy crop were restricted using the aggregate of these two constraint masks.

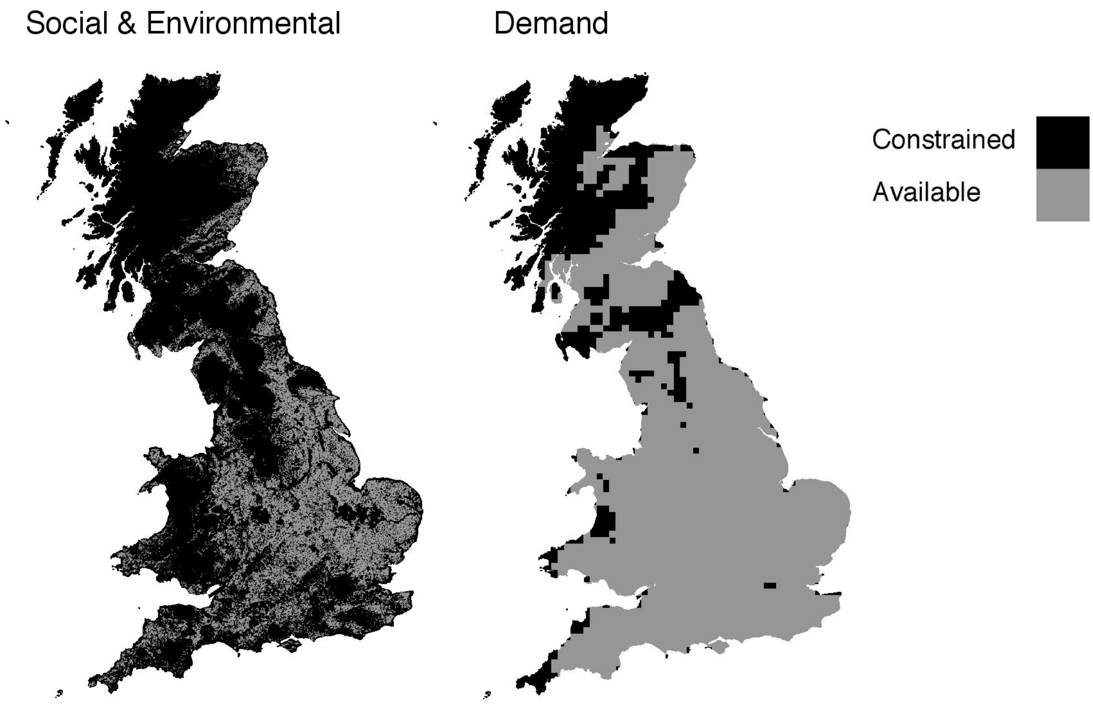


Figure 3-5: Social & environmental and demand constraint maps for energy crops. Data sources: Lovett *et al.* (2014) and Wang *et al.* (2014).

3.3.5 Yields under climate change scenarios

The modelling of responses to climate change scenarios required yield estimates for all crop activities under each scenario considered. The impact of such changes will vary spatially so an approach to assessing the impact that takes account of variation by location was required. Butterworth et al. (2010) looked at effect of climate change on oilseed rape yields. They estimated the adjustment to these yields at a regional level for England and Scotland using UKCIP02 (Hulme *et al.*, 2002). The treated oilseed rate percentage adjustments results were used for all climate scenario conventional agricultural crop variations. The data for Wales was unavailable so the results for West Midlands were used for that region. The energy crop yield distribution were produced under the UKCIP09 climate scenario by Hastings *et al.* (2014) and Tallis *et al.* (2012). After the same resampling process as described for the baseline case, these were input into the spatial model allowing the supply curves and distribution to be generated for each climate change scenario.

3.4 Results

3.4.1 Baseline UK energy crop supply

3.4.1.1 UK aggregate supply

UK supply curves for these perennial energy crops were generated by running the model with a range of Miscanthus and SRC willow prices. A farm plan, giving the optimum level of all activities, was generated for each 1km^2 farm, farm-gate price and climate scenario. A point on the supply curve was found by summing each value for each energy crop across a given geographic area for that farm-gate price and climate scenario. The separate energy crop prices were adjusted using the LHV to maintain a consistent usable biomass energy price from combustion. Supply can be expressed in terms of area used for crop production, supplied mass or supplied energy. Figure 3-6 shows the UK supply curve for the two perennial energy crops in terms of mass supplied per annum. The scales of the Miscanthus and SRC willow price axes have been chosen so that the price per net calorific energy is equal. Examining the annual supplied mass, at low supply amounts then SRC willow dominates the mix of energy crops. SRC willow accounts for 94% of the economic energy crop area at a SRC willow price of £32 odt^{-1}, the Miscanthus LHV equivalent price is £40 odt^{-1}. At higher supply rates and correspondingly higher prices, Miscanthus accounts for an increasing proportion of supply. At an estimate of current market prices of £60 odt^{-1} for Miscanthus, 70% of energy is supplied from that crop, from 65% of biomass using 66% of the area selected. The dominance of Miscanthus in the economic supply of biomass from perennial crops increases further with higher prices and supply rates, at a price of £80 odt^{-1}, 79% of the energy is from that source.

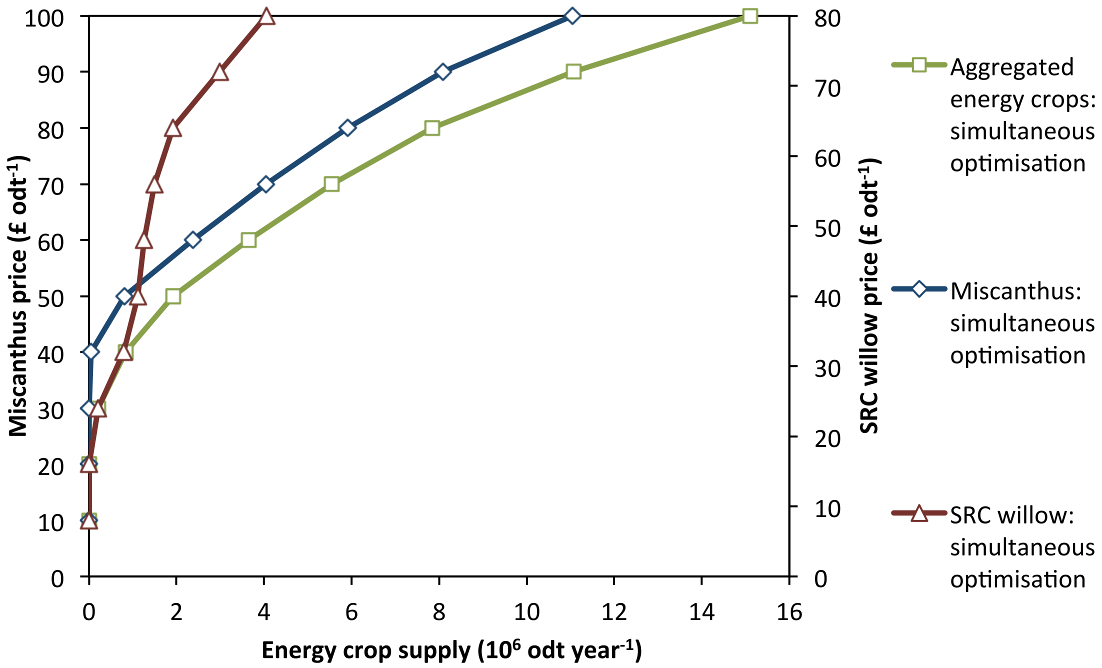


Figure 3-6: Miscanthus, SRC willow and aggregate supply mass for the UK using baseline data, with energy crops optimised simultaneously.

3.4.1.2 Regional variations of supply

The UK supply curve loses the spatial variability of the results. The low energy density of these energy crops results in a high cost of transport (Borjesson & Gustavsson, 1996), making the distribution of the supply an important consideration. To provide a visualisation, Figure 3-7 shows the area percentage of energy crop selected, for both energy crop, mapped across the UK, using currently estimated market prices and baseline climate data. These maps of economic energy crop selection demonstrate that both crops do have highly regionally specific behaviours. The South West region of England appears to dominate Miscanthus selection, while the North West region dominates SRC willow selection.

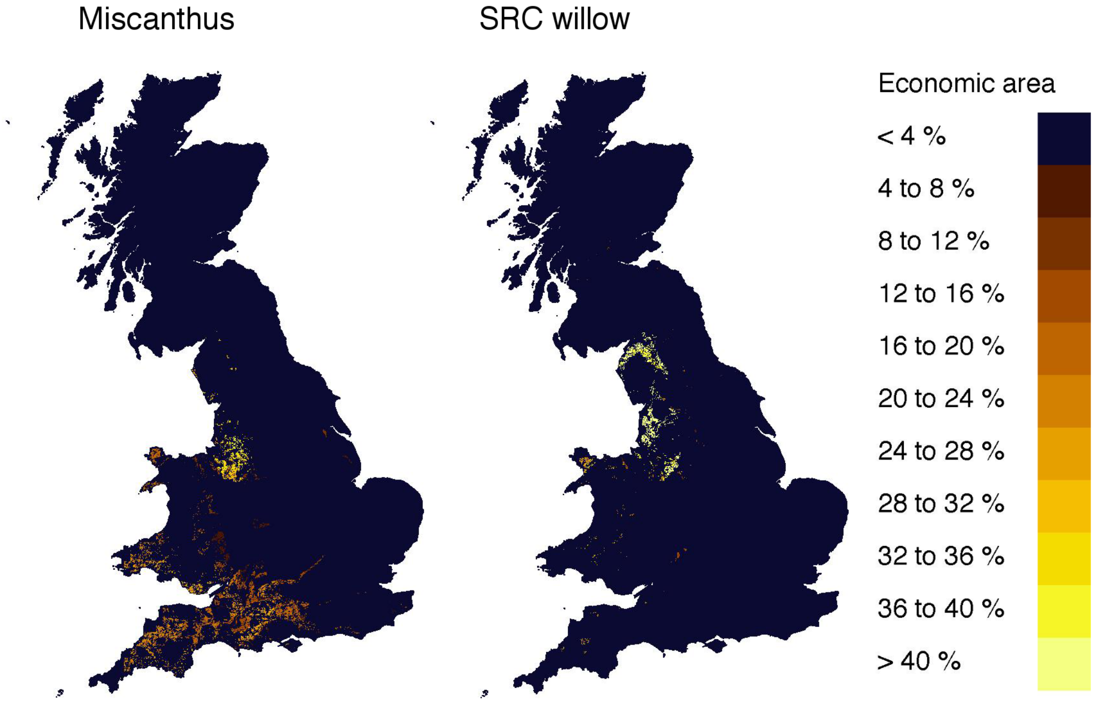


Figure 3-7: Economic energy crop supply distribution maps, optimised concurrently, using the baseline scenario at current market prices for Miscanthus (£60 odt^{-1}) and SRC willow (£48 odt^{-1}).

To quantify the regional differences in behaviour the supply was aggregated at that level. Again taking a price of £60 odt^{-1} for Miscanthus, and the LHV equivalent price of £48 odt^{-1} for willow SRC, the results show that 52% of UK Miscanthus supply mass is from the South West of England and 85% of SRC willow supply is from the North West of England, produced from areas of 85 kha of Miscanthus in the South West and 77 kha of SRC willow in the North West of England. Under this scenario, a total area of 260 kha was selected for energy crops. Table 3-2 shows these and the other regional figures for the UK, including supply expressed in area, mass and energy terms and the mean yields for each area. Figure 3-8 shows the supply curves by mass aggregated at a regional level for Miscanthus and SRC willow, again demonstrating the highly regionally specific behaviour.

Table 3-2: Regional supply quantities and mean yields at a Miscanthus price of £60 odt^{-1} and an SRC willow (SRC) price of £48 odt^{-1}.

Region	Misc. supply (1000 odt year^{-1})	SRC supply (1000 odt year^{-1})	Misc. area (kha)	SRC area (kha)	Mean Misc. Yield (odt year^{-1})	Mean SRCW Yield (odt year^{-1})	Misc. Energy (PJ year^{-1})	SRC Energy (PJ year^{-1})
East Midlands	2	1	0	0	14.1	17.0	0.03	0.01
Eastern	2	0	0	0	15.1	-	0.03	0
North East	0	3	0	0	-	16.4	0	0.04
North West	413	1083	34	77	12.0	14.1	6.29	13.11
Scotland	0	3	0	0	-	17.1	0	0.04
South East	258	0	16	0	15.9	-	3.92	0
South West	1235	37	85	3	14.6	14.7	18.78	0.45
Wales	427	117	31	8	13.7	15.4	6.49	1.42
West Midlands	36	8	3	1	12.2	14.2	0.55	0.09
Yorkshire & Humber	7	16	1	1	13.8	16.8	0.11	0.19
Total	2380	1268	172	89	14.0	14.2	36.20	15.34

(a)

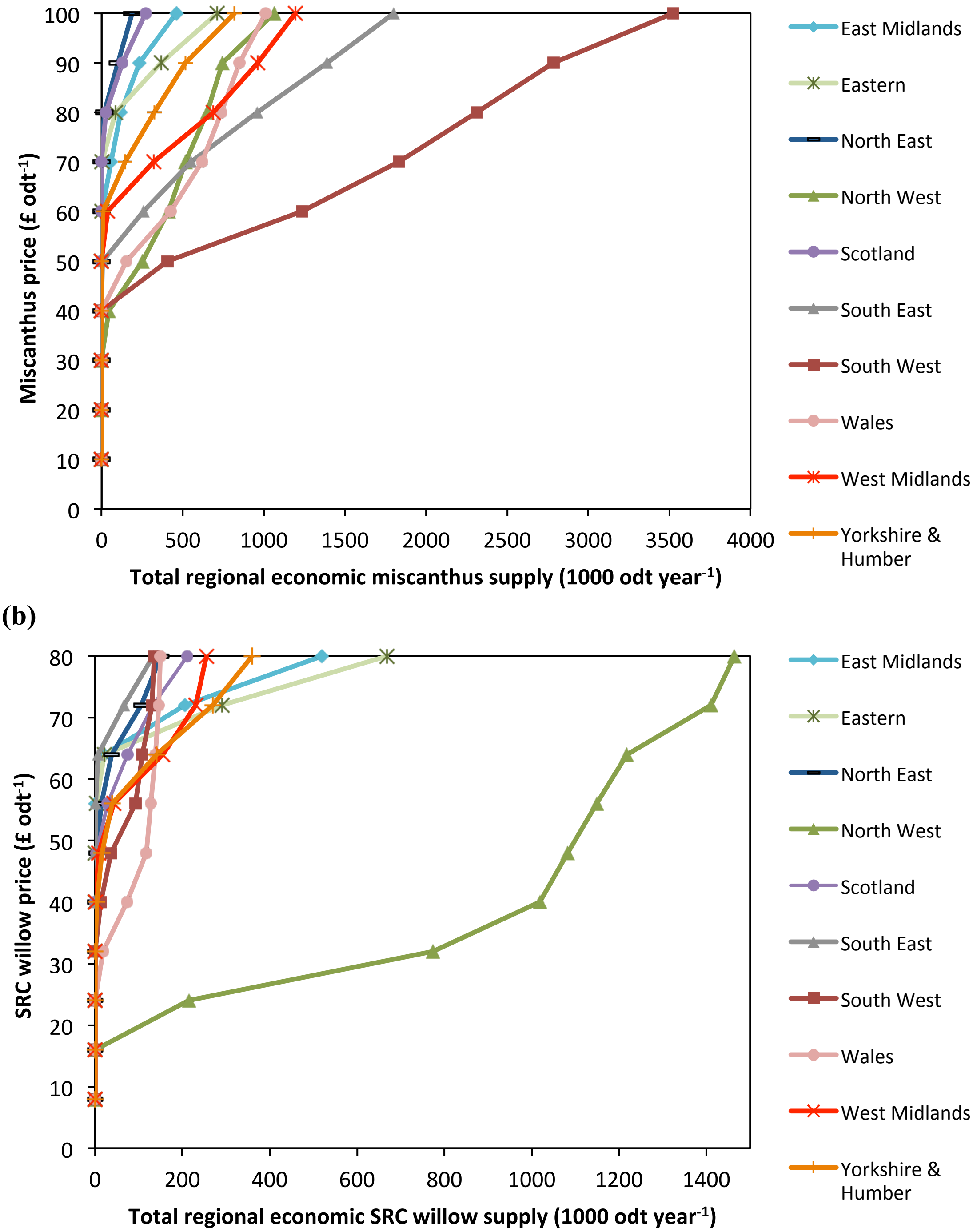


Figure 3-8: Regional breakdown of (a) Miscanthus and (b) SRC willow supply curves for the UK using baseline data, optimised simultaneously.

To provide an indication of the relative ability of each energy crop to act as a substitute, and whether there was direct competition for the select on the same land, the model was also run with selection of each energy crop suppressed in turn. The results of these runs were compared against optimisation where both energy crops were available (Figure 3-9). As expected the aggregate supply is greatest where both crops are available for optimisation. However the reduction in supply by removing the option to select SRC willow is relatively small at high supply rates. For example at £90 odt^{-1} Miscanthus price the reduction in aggregate energy supply is 12%, by removing the option to select SRC willow. At the equivalent price of £72 odt^{-1} SRC willow price the aggregate is reduced by 62% by the suppression of Miscanthus and allowing only SRC willow selection.

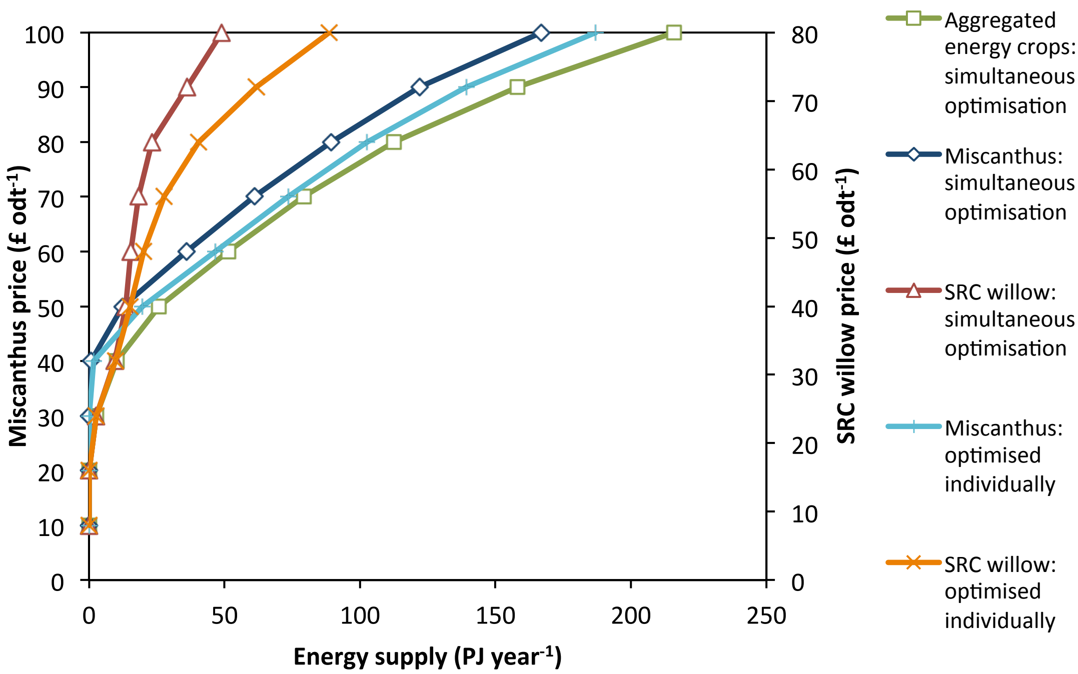


Figure 3-9: Energy supply for the UK from energy crops, using optimisations with Miscanthus only, SRC willow only and both energy crops simultaneously.

3.4.2 Climate change impact on supply

The model was run using yield estimate distribution under various climate change scenarios. The supply curves from the baseline and low emission scenarios are shown in Figure 3-10. Climate change reduces the economic area of SRC willow, with the effect increasing as climate changes into the future. The opposite impact is seen with Miscanthus, with the baseline case producing the least economic area for a given price. The impact for SRC willow is greater and more systematic in comparison to that of Miscanthus. The SRC willow area decreases over time, while the Miscanthus area decreases initially, until 2020, and then remains broadly static. There are significant regional and crop variations in adjustment to climate change, making generalisation difficult. To separate what level of change resulted from energy crop adjustment and that resulting from the conventional crop adjustments, the model was run with no adjustment made for conventional crops. The results show the same directional change as shown in Figure 3-10, but the response for SRC willow was lower, and that for Miscanthus was greater. The Miscanthus response to climate change also increased over time. Figure 3-10 also shows the results from all 2030 climate scenarios, with similar behaviour noted under the 2020 and 2050 scenarios.

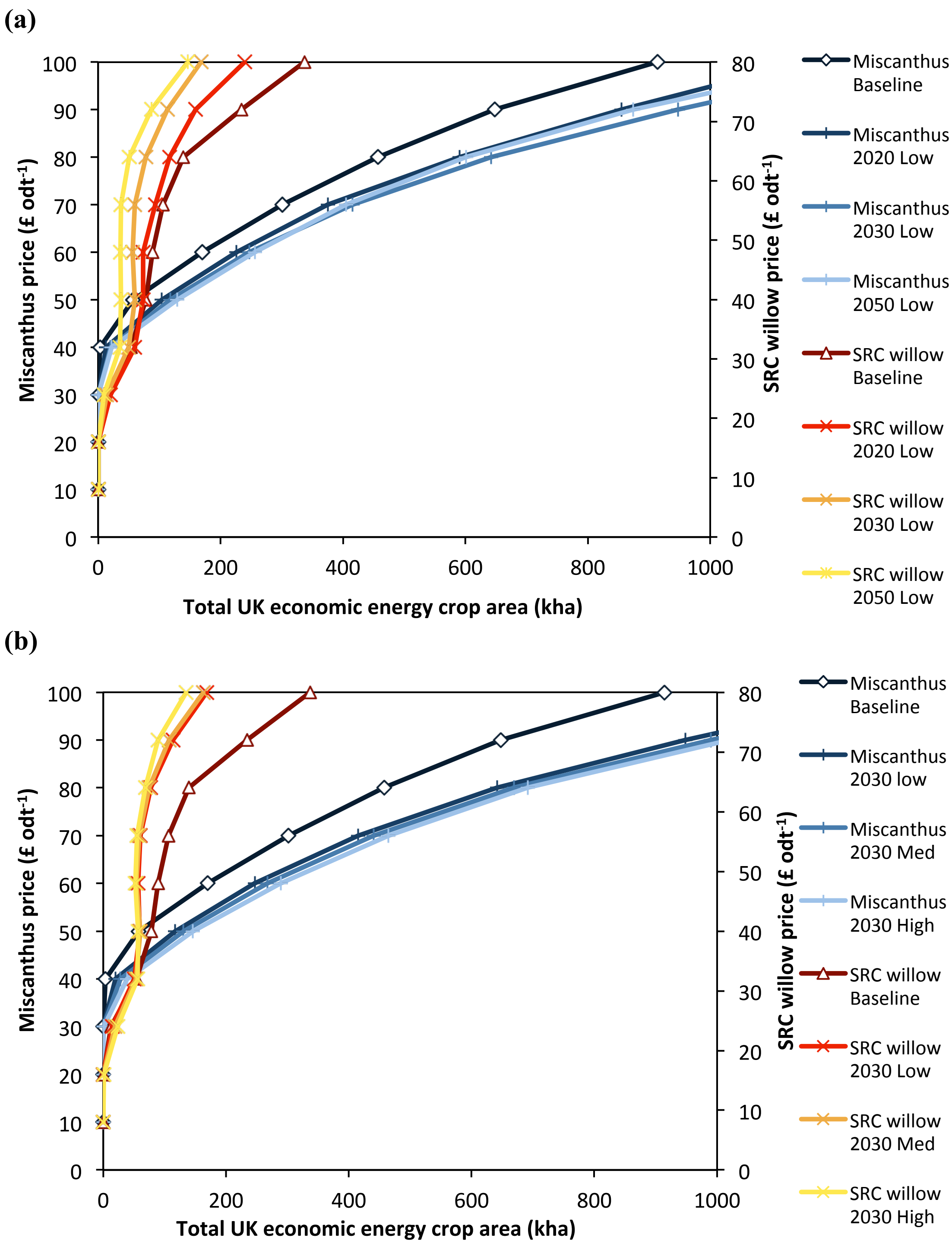


Figure 3-10: UK total perennial energy crop supply curves (a) under 2020, 2030 and 2050 low climate change scenarios, and (b) under high, medium and low emission scenarios for 2030.

3.4.3 Risk-aversion sensitivity

The sensitivity to the risk-aversion parameter over the range of 0.0 to 2.0 was determined by running the model for the baseline case with a range of risk-aversion parameters. Figure 3-11 shows supply curves of the economic area for Miscanthus from runs with Miscanthus optimised only.

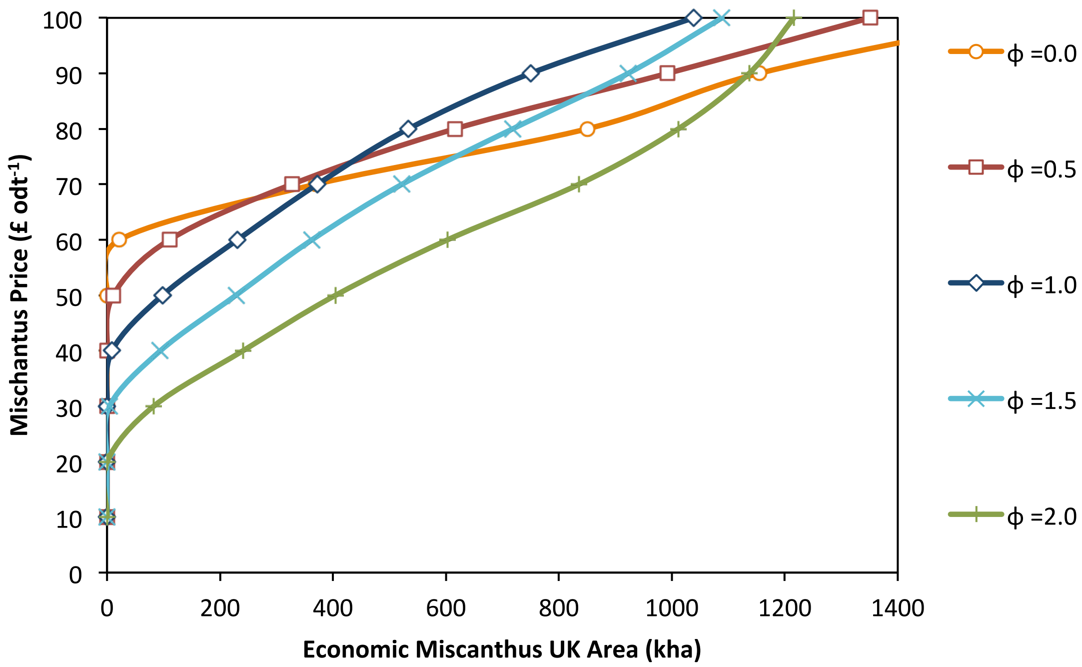


Figure 3-11: Sensitivity of economic UK area for Miscanthus to variations in risk-aversion parameter.

As an indication of sensitivity to the risk-aversion parameter, the price that provides an economic area equal to the target area of 350 kha (DEFRA, 2007) was determined. This was done by linear interpolation between the two price points either side of the target area. Table 3-3 shows the required prices and the percentage change in price from the central estimate of a risk-aversion of 1.0.

Table 3-3: Miscanthus prices required to provide 350 kha of economic Miscanthus selection for a range of risk-aversion parameters (φ).

	φ =0.0	φ=0.5	φ=1.0	φ=1.5	φ=2.0
Miscanthus price (£ odt^{-1})	£69.44	£70.79	68.41	59.03	46.66
Change from baseline φ=1.0 (%)	1.5	3.5	-	-13.7	-31.8

Both Figure 3-11 and Table 3-3 suggest that the total supply does not show a particularly high sensitivity to the risk-aversion parameter in the range 0.0 to 1.5. The reason for this appears to be that two opposing effects occur with adjustments to risk-aversion. As risk-aversion reduces, the number of farms that select energy crops decreases, but a significant reduction in supply does not occur as it is counteracted by an increase in selection rate at those farms that do select. At very high risk-aversions, above 1.5, the incentive to diversity increases, as the risk component starts to dominate. So at lower energy crop prices, the selection is increased in scenarios with high risk-aversion compared to those with low risk-aversions; farmers are more willing to take a lower profit for a reduction of risk. At higher prices lower uptakes are seen, as the preference is still to keep a diversified crop selection, though at these prices, Miscanthus often has the highest gross margin.

At zero or low adoption rates (see Figure 3-11), energy crop prices are ordered by risk-aversions, with lower energy crop prices associated with higher risk-aversion. As the area of adoption increases, the order changes. At the greatest adoption rates produced, the zero risk-aversion case has become associated with the lowest energy crop price. Although the reversal of order is not fully completed for all risk-aversions, over the range of prices tested, at a high adoption level, lower energy crop prices are generally associated with lower risk-aversion.

To understand the reasons behind this reversal in order, we will consider the two extremes of risk-aversion, and how the adopted area changes with increasing energy crop price. With zero or low risk-aversion, the selection of crops (or crop rotations) is determined by which has the highest gross margin. Once the energy crop price has increased to a level where the energy crop gross margin is the greatest, then full adoption will occur for that farm, as there is no incentive to diversify (as risk is unimportant) and no rotational constraint for the energy crops. The rate of adoption increases with the energy crop price as further farms, with increasingly lower energy crop yields, are found to have an energy crop gross margin higher than for any conventional rotation. The shape of the curve is influenced by the frequency distribution of energy crop yield areas. Miscanthus selection starts from £60 odt^{-1}, as there are no farms where Miscanthus has the highest gross margin at a lower price. As prices increases the full adoption of farm causes a relatively rapid rate of increase in adoption.

This ‘all or nothing’ adoption pattern is in contrast to that with a high risk-aversion. The higher the risk-aversion the greater the incentive to diversity, and accept a reduction in the expected gross margin. The consequence is that adoption starts at a lower price (£30 odt^{-1}). However, the need to diversity means that even at higher energy crop prices a range of crop activities is maintained, see Figure 2-2 and Figure 2-4. As a result the increase in adoption, with increased price, is slower than for the zero risk-aversion cases. This behaviour causes the reversal of risk-aversion order seen in Figure 3-11.

3.5 Discussion

3.5.1 Input data issues

The input data used for conventional crop yields and climate change adjustments is not considered ideal. Due to lack of higher resolution data the baseline conventional crop yields are from regional data, while the energy crops have yield estimates at a 1km^2 scale. This may create a positive bias for the selection of energy crops in some regions and a negative bias in others. In regions with relatively low average conventional crop yields, a bias may result towards selecting the better quality sites being selected for energy crops, as the yield predictions for the energy crop is able to take this into account while the regional mean yields on conventional crops cannot capture that variation. However in the regions with high mean conventional crops yields this is reversed, with the relatively poor yielding areas that may be suitable for energy crop selection may fail to be selected, hence creating a negative bias. Differences in biophysical growth properties of the crops may reduce or remove such an affect. It is difficult to quantify the impact of these effects without having a more disaggregated set of conventional crop yield data over which to run an analysis. The regional yield data comes from three sources (DEFRA, Welsh Government and Scottish Government), which may lead to inconsistencies in methodologies or data gathering approaches. Further the data for Wales was for the 2009 harvest, while other regions were for 2010, due to lack of published data for that year for Wales.

Another issue with the conventional crop yield data relates to using the OSR climate adjustment factors for all conventional crops. This is an approximation borne of the lack of factors for each crop. Comparing the results using these adjustments and where no conventional crop adjustment shows that in areas important for energy crops production the conventional crop adjustments provide a net increase in yields. However this is smaller than the net increase in the yields for Miscanthus. In the case of the SRC willow the response to climate change is negative, while the conventional crop adjustment tends to increases yields, which generates a greater reduction in SRC willow selection. Despite some concern about the conventional crop adjustments used, the response to climate change for each crop is clear, and that the response is greater than that predicted for OSR.

The assessment of risk of a portfolio of crops is calculated using variance and covariances calculated from a historical dataset over a 20 year period, assuming the energy crop prices correlate to oil prices (Alexander & Moran, 2013). It has been suggested (FAO, 2008) that arable prices have become more correlated to oil price, although there is evidence of a complex relationship (Nazlioglu, 2011). If the historical data underestimates farmers' perception of these price correlations, then the model will also underestimate the farmers' expected correlation between energy and arable crop incomes. In situations where energy crops have a lower expected gross margin the result would be a bias towards lower modelled economic energy crop area, as the modelled incentive to diversify with these crops is reduced. Where the energy crop has a higher gross margin the opposite effect would occur, because similarly the incentive to maintain a diverse set of activities using arable crops is also reduced.

The costs of agricultural activities have been modelled using contractor rates, but many farm business use on-farm labour and machinery, which may form a barrier to energy crop adoption (Sherrington *et al.*, 2008). There are a number of reasons to believe that this cost assumption will not significantly impact the results presented here. Firstly, a relatively large change in labour and machinery costs is unlikely to influence the results significantly, as the cost of labour and machinery are only a proportion of total input cost (39% for wheat), and the farm-scale model is less sensitive to input costs than to crop yields or prices (Alexander & Moran, 2013). Secondly, if farm labour or machinery becomes available due to switching of cropping activities then these can be made use of off-farm, for example by conducting contracting work for other farms (14% of holding in England already are involved with some form of contracting or haulage (DEFRA, 2012)), or selling of redundant machinery. Thirdly, such issues only form a transient barrier to adoption that is not represented by this analysis. Another potential issue is the inclusion of sugar beet in the potential agricultural activities, without constraints to only selecting in areas where processing facilities exist. However, the low sugar beet uptake (Alexander & Moran, 2013) suggests that it is unlikely to materially affect the results.

3.5.2 Comparison between SRC and Miscanthus

The results show that SRC willow dominates the mix of energy crops at a low energy crop price, but that with higher prices Miscanthus accounts for an increasing proportion of supply, and at a sufficiently high price the majority of supply is provided by Miscanthus. The Miscanthus area as a percentage of the total energy crop is just 6% at a Miscanthus price of £40 odt^{-1}, but increases to 76% at £80 odt^{-1}. The reason is that there is a small area of SRC willow estimated with very high yields (>17.5 odt ha^{-1} year^{-1}), located mostly in the North West of England (Figure 3-3). These areas coincide with relatively low cereal yields (Figure 3-2), and so are selected by the farm-scale model at relatively low crop prices, down to £24 odt^{-1} for

SRC willow where 12 kha is economic. However these areas are relatively limited and once they have been selected, the SRC willow yields on the remaining areas quickly reduces. Miscanthus on the other hand has no areas with such high yields predicated, but a greater area with a more moderately high yield (>14.5 odt ha^{-1} $year^{-1}$). It also has the advantage of a higher crop price, with relatively similar establishment costs, in comparison to SRC willow. As a result, at a sufficiently high price for Miscanthus to become economic in these areas, a greater uptake is supported.

The results suggest that at a UK level SRC willow is only likely to be able to supply a small proportion of the anticipated perennial energy crop target, without increases in market price. The economic area for SRC willow calculated, acknowledged to be a ceiling on actual uptake, does not reach the target until over a price of £80 odt^{-1}, nearly double current market levels. Actual uptake will, as previously discussed, be further limited by other considerations. Miscanthus appears to have greater scope for supply, to have an economic area for production equal to the target requires a price of £73 odt^{-1} a 22% rise from current market levels. The rate of increase in economic areas to a rise in market price is also greater for Miscanthus than SRC willow, above £40 odt^{-1}. The different impacts of climate change on each crop (Figure 3-4), further suggests the likely larger role for Miscanthus than SRC willow.

The impact of climate change, under all emission scenarios, is to significantly reduce the economic supply for SRC willow, even by 2020 (Figure 3-10). At current market levels the area of SRC willow is reduced to just 41% of baseline levels under the low emission 2050 scenario, and only 32% in the high emissions scenario. Even in the 2020 low emission scenario a reduction to 83% of the baseline level results. The rate of reduction increases with higher biomass prices. In contrast, the supply Miscanthus increases under all climate scenarios. At 2050 a 50% and 47% increase in selected area from the baseline is seen under the low and high emission scenario respectively, at current market prices. The 2020 low scenario has a 34% increase. The aggregate result in an approximately 10% rise in total energy crop selected area in each of these scenarios. These changes are being driven by the relative yield change in the energy crops and the other agricultural activities. Figure 3-4 demonstrates that the impact of climate change on the two energy crops is complex, but that broadly the Miscanthus yields are increased, with many areas having substantial gains (>4 odt ha^{-1} $year^{-1}$). SRC willow has a more mixed picture with limited areas seeing increases, and most areas having reduced yields. In all climate change scenarios SRC willow supply is reduced and Miscanthus is increased, suggesting that the initial dominance of Miscanthus may be amplified over time.

Miscanthus represents 66% of the total has an economic area, at the current market price and baseline climate, with a Miscanthus area of 172 kha and SRC area of 89 kha. Under the low 2050 climate change scenario the areas change to 256 kha and 36 kha respectively, or 88% of the area as Miscanthus. The actual planting of these crops from 2000 to 2011, under the energy crop schemes, was 7365 ha of Miscanthus and 1847 ha of SRC (Natural_England, 2006, 2011). This implies that 80% of the actual energy crop area was established as Miscanthus. The agreement in the relative dominance of Miscanthus, between the model results and the actual crop establishment, is encouraging for the plausibility of these results. The difference in the absolute level of uptake is discussed below.

3.5.3 Level of uptake

The model outputs give an indication of the amount and distribution of Miscanthus and SRC willow crops that could be economically grown at a given farm-gate price for biomass energy. These results cannot be seen as a prediction of farmer's uptake of these crops under a given scenario, as many other factors are involved that limit uptake and act to constrain it, for example attitudes to novel crops and distances to an available market. Despite this, the results do suggest a potential maximum limit on uptake, as crops are unlikely to be widely grown where they are not economic in comparison to alternative activities. Some of the factors that may be involved in restricting the selection of these energy crops are: the availability of a market into which they can be sold, the distance to these markets, and farmer's willingness to choose an innovative crop. These factors would be expected to diminish in possible significance as the size and spatial reach of the market increases.

The UK Biomass Strategy identifies the prospect of part of the increased supply coming from a major expansion of UK production in perennial energy crops, potentially using 350 kha, an area equivalent of 6.5% of total arable land (DEFRA, 2007). Linearly interpolating between results, to obtain an economic area of this scale in aggregate between these crops requires a price of £66 odt^{-1} for Miscanthus and the equivalent price of £53 odt^{-1} for SRC willow. These prices are somewhat higher than current market levels, around 8% in both cases. However the actual uptake has been comparatively limited, at around 17 kha (RELU, 2009). Although this figure is somewhat out-of-date, more recent figures from Natural England suggest that no increase in the rate of planting has occurred subsequently; in fact their data implies a reduction in the rate of establishment. During the period 2000-6, grants to establish a combined area of 8191ha where provided in England, while in the period 2007-11 only 1305 ha received establishment grants (Natural_England, 2006, 2011).

At current market prices, the indicated economic area is 260 kha. Taking the current area as 17 kha (RELU, 2009), this implies that only 6.5% of economic sites are actually being selected to grow the crops. There are many reasons that have been postulated for why uptake has been slow (Sherrington & Moran, 2010). The model presented here includes a risk model to provide some representation of this aspect; however, it does not attempt to include either the barrier to adoption of the innovation that these crops represent or the lack of a market into which farmers can sell their production. Adoption of previous novel crops has shown long time lags, despite an apparently positive economic case. For example, the adoption of oilseed rape show time lags of 15-20 years when the price of oilseed rape stabilised and increased due to the intervention price structure after UK entered the European Economic Community in 1973 (Wrathall, 1978; Allanson, 1994; EDINA, 2012). The adoption over the following 25 years displays the typical S-shaped curve of a diffusion of innovation process (Rogers, 1995). Such time lags suggest that adoption and diffusion of innovation behaviour may be important for the update of energy crops.

Without a readily available and accessible market there would seem little likelihood that the crops will be established. The relatively low energy density of these crops exacerbates the issue, as it means that transportation costs are high and so that economic distances that the material can be transported are commensurately low (Borjesson & Gustavsson, 1996). Local demand is therefore needed into which the produced crops can be delivered at a viable cost (Wang *et al.*, 2014). The low level of uptake suggests that efforts to encourage market development may be important in meeting the aspiration for UK energy crop growth. The 'chicken and egg' problem appears as significant barrier, where farmers are not willing to grow the crops without a more mature market and potential investors are not willing to develop the plants and technologies that are required to create the demand and so establish the market (Sherrington *et al.*, 2008). The cyclic contingent behaviour between farmers and plant investors increases the complexity of the overall system, making analysis more difficult.

The previous non-spatial analysis (Chapter 2) provides an estimate of the economic rate of energy crop selection, for a given energy crop price, crop yields and risk-aversion. A non-spatial estimate of the UK economic adoption can be obtained, by applying the rate of selection using mean yields, to the area of suitable land in the UK. Taking the current market prices for the each energy crop and the average crop trial yields (12.8 and 9.7 odt ha^{-1} $year^{-1}$ for Miscanthus and SRC willow respectively, see Chapter 2), gives zero adoption for both energy crops, at a baseline risk-aversion (Figure 2-2 and Figure 2-4). Over the most plausible range 0.5-1.5 (Hazell & Norton, 1986), only Miscanthus shows any selection at 1.5, at a rate of 4%. Assuming a uniform distribution of preferences over this risk-aversion range, suggests that 9% of farmers would have a value of 1.5, given the 0.1 increments used. However, the risk-aversion distribution is likely to be more concentrated at the central figures, so this may be an over-estimate. Applying these figures to the total area of 8.5 Mha believed available for these crops in the UK (Lovett *et al.*, 2014), gives an estimated area of adoption of 30 kha of Miscanthus and no SRC, suggesting that there would only be limited adoption except at sites with higher than average energy crop yields (or lower than average conventional crop yields). To generate an estimate of the UK adoption, including variation in crop yields, the frequency distribution of the combination of energy and conventional crop yields is needed. The analysis presented in this chapter involves such an evaluation.

3.5.4 Regional variations

A high degree of regional concentration in supply is demonstrated by the results; see Table 3-2 and Figure 3-8. The distribution of energy crop selection appears primarily due to the relatively high energy crop yields, tempered by the yields on the other agricultural activities. Figure 3-3 shows that many areas of high SRC willow yields are in Wales and the North West of England. However most of these areas in Wales are unavailable due to the socio-environmental constraints (Figure 3-5). The result is the North West of England leads the supply of this crop, with 85% of supply at assumed prices. Other regions do not have many areas with yields high enough to allow the returns for this crop compete with the returns of the other crops. The relatively high yielding areas for Miscanthus (>14.5 odt ha^{-1} $year^{-1}$) are focused around the South West of England, but extend north and east. The economic areas for Miscanthus also include areas where the yields on that crop are not quite as high (between 11.5 and 14.5 odt ha^{-1} $year^{-1}$), primarily in the North West of England. These areas appear to be economic due to the relatively lower yields on conventional crop activities, however it remains the South West of England that provides the majority of supply (52% at £60 odt^{-1}).

The regional concentration in supply may be beneficial in regard to creating the conditions required to establish locally viable market for these crops, in the regions where significant economic supply exists. The high transportation costs make small supply distances desirable, both from a financial and GHG standpoint. However sufficient supply is required to make construction of facilities to consume these crops for direct power generation or pelletisation, implying benefits in having locations where there is a high density of land used to produce the crops. More work is needed to understand the dynamics between the distribution of supply and the potential locations of plants. Such work would address deficiencies in the current analysis, allowing further insights to be gained into the barriers that limit the market development. For example, the current model limitation on having a homogenous farm-gate price would have to be addressed, by determining and accounting for the cost for transportation between supply and demand locations. A dynamic model that supports the representation of market growth, including out of equilibrium market conditions would also be required to study the potential patterns of growth and the factors that influence it. Modelling of a market with contingent behaviour can be problematic with traditional methods and the spatial aspects of the system further increase the complexity. An agent-base modelling approach may be suitable as it has previously been used to dynamically model other spatial systems with contingent behaviour (Dibble, 2006).

3.6 Conclusions

These results suggest Miscanthus has a higher rate of potential economic supply, in comparison to SRC willow, implying that it may be a more significant crop in the production of biomass. The response to climate change scenarios further favours Miscanthus, suggesting that Miscanthus supply increases under future climate, while SRC willow supply is expected to reduce. The economic areas using current market prices are far in excess of crop uptake to date, suggesting that significant barriers to market adoption may exist, potentially involving the lack of farmers' access to a local market for the crop. Highly regional specific behaviour was noted, which may assist market development within areas with the highest concentration of potential economic supply. To understand the dynamics of the interaction of farmers choosing to grow the crop, and investors choosing to build the consuming plants, further modelling work is required to represent the behaviour of the market as a whole. An example of such work is presented in chapter four.

CHAPTER FOUR

THE ROLE OF SPATIAL DIFFUSION

After article: Alexander P, Moran D, Rounsevell M, Smith P (2013) Modelling the perennial energy crop market: the role of spatial diffusion. *Journal of the Royal Society Interface*, 10. See Appendix III.

4.1 Abstract

Biomass produced from energy crops, such as Miscanthus and short rotation coppice, is expected to contribute to renewable energy targets, but the slower than anticipated development of the UK market implies the need for greater understanding of the factors that govern adoption. Here we apply an agent-based model of the UK perennial energy crop market, including the contingent interaction of supply and demand, to understand the spatial and temporal dynamics of energy crop adoption. Results indicate that perennial energy crop supply will be between six and nine times lower than previously published, because of time lags in adoption arising from a spatial diffusion process. The model simulates time lags of at least 20 years, which is supported empirically by the analogue of oilseed rape adoption in the UK from the 1970s. This implies the need to account for time lags arising from spatial diffusion in evaluating land use change, climate change (mitigation or adaptation) or the adoption of novel technologies.

4.2 Introduction

Bioenergy is expected to contribute to the UK's target of deriving 15% of energy from renewable sources by 2020 (DECC, 2011a). To achieve this, annual growth of 9% is required for the biomass sector (DECC, 2011a), with the greatest growth in domestic biomass supply coming from agricultural residues and energy crops (DfT *et al.*, 2012). UK perennial energy crops would potentially occupy 350 kha, equivalent to 6.5% of the total arable land area (DEFRA, 2007). However, despite the existence of financial incentives supporting establishment, the area of UK perennial energy crops is comparatively limited, at around 17 kha in 2009 (RELU, 2009). Continued slow uptake is evident with an area of only 1305 ha receiving establishment grants in England for the period 2007 to 2011 (Natural_England, 2011). The low adoption of these crops suggests the need for greater understanding of the behaviour of this nascent market. To date, most studies on energy crop markets focus either on optimising demand where supply is exogenously given (Dunnett *et al.*, 2008; Yagi & Nakata, 2011), or investigating the supply distribution for an assumed level of demand (Aylott *et al.*, 2008, 2010; Yemshanov & McKenney, 2008; Bauen *et al.*, 2010; Wang *et al.*, 2011). Although some studies have used a spatially explicit model of biofuel crops (Hellmann & Verburg, 2011), no studies have considered the economic case for each participant within the supply chain, or represented price movements of the market that are potentially in disequilibrium. Moreover, if farmer behaviour and preferences are thought to be important for adoption (Sherrington & Moran, 2010), these need to be included more fully in models to understand market dynamics.

The energy crop market has a number of features that need to be represented within a model. First, energy crops compete against conventional agricultural activities for farmer selection. Soil, climate and other spatially variable factors mean that crop selection varies by location. It is desirable to undertake analyses at a fine spatial resolution to capture these influences, but this makes determining an optimal solution difficult (Dunnett *et al.*, 2008; Chen *et al.*, 2010). In addition, individual farmers' perceptions and preferences affect selection behaviour. Behaviour varies between farmers, and changes over time through experience (Guillem *et al.*, 2012). Second, the cost of transporting energy crops is high, due to their relatively low energy density (Borjesson & Gustavsson, 1996; Dunnett *et al.*, 2008). Third, power plant investment is required to construct and operate facilities that consume energy crops and convert them into electricity, heat, heat and power, fuel pellets or bio-fuels. Each biomass plant must be located appropriately to ensure demand for their outputs and be expected to have sufficient supply available at an economic price, for their operational life. Proximity of plants to available feedstock is a critical factor in the efficient utilisation of the resource, and often dictates the technology and size of the proposed project (Hellmann & Verburg, 2011; Mott MacDonald, 2011).

Representing the contingent behaviours between supply and demand, and the disequilibrium in market conditions that are likely to arise, adds further complexity. It is doubtful that an investor will choose a plant site without first being convinced that sufficient supply can be obtained for the lifetime of the plant at an economically viable cost. Similarly, farmers are unlikely to select a crop unless a market exists into which they can sell. No previous studies have represented this contingent interaction between farmers and plant investors; a relationship that is likely to be key in understanding the rate of market expansion and the eventual level of adoption.

An ABM was selected to model the perennial energy crop market. ABM allows the dynamic representation of decision-makers and their interactions, often within a spatial framework. From an initial state, the system evolves over time, based on the behaviour of the agents and their interactions with their environment and one another (Rounsevell *et al.*, 2012). The spatial and dynamic behaviour of complex system can then be investigated, which many other modelling approaches find intractable (Zimmermann *et al.*, 2009). ABM techniques have been applied to a wide range of areas and disciplines, these include those involving human decision-making and those that do not (Macal & North, 2010), from vigilance patterns in gulls (Beauchamp *et al.*, 2011), through epidemiology (Perez & Dragicevic, 2009), to representing contingent behaviours (Dibble, 2006). Within the agricultural sector, ABM has been commonly used for modelling of land-use and land-cover changes (Berger, 2001; Parker *et al.*, 2003; Matthews & Bakam, 2007; Soman *et al.*, 2008; Bone *et al.*, 2010; Chen *et al.*, 2010). Farm-scale modelling takes a micro perspective, while conventional sector models using mathematical programming or econometric approaches work from the top-down (Bone *et al.*, 2010), but ABM supports the two-way interaction of behaviour between these scale levels (Happe, 2004). It also has the ability to capture the non-linear behaviours of market dynamics, while not predicating the need for potentially overly simplistic behavioural assumptions (The Economist, 2010). A further strength of ABMs is the possibility to capture path-dependence, or hysteresis, in systems behaviour (Bonabeau, 2002). As a result this class of model is perhaps uniquely suited to representing the complex system of the developing energy crop market.

There are however a number of weaknesses of ABMs, perhaps the biggest of these are the potential level of complexity, and associated problems with validation. There is a risk that ABMs can become overly complex, due to the increased flexibility and the desire to model all the factors (Zimmermann *et al.*, 2009). As a result it can become difficult to establish a connection between cause and effect and to link the model to the real-world system, reducing their explanatory power (Happe, 2004; Ghoulmie *et al.,* 2005). A more parsimonious approach is beneficial where the model generates stylised properties consistent with the observed data; although potentially desirable, this may not be possible in all cases. Another consequence of their complexity is that ABMs can be difficult to validate. Knoeri *et al.* (2011) argues that comparing ABM performance with empirical system data is often not possible and therefore it is necessary to focus on conceptual model validation. Batty & Torrens (2005) see the need to use more qualitative assessments in such cases. The number of assumptions often required and issues with validation may make it impossible to use the ABMs to make predictions. However they provide a simulation tool, to understand mechanisms, demonstrate what is possible, and to facilitate greater discussion (Batty & Torrens, 2005).

4.3 Materials and methods

The model used here comprises two groups of agents: farmers and biomass power plant investors. Plant investor agents make decisions to invest in the construction and operation of power plants to consume energy crops. They must select the type, size and location of plants to construct and operate. In aggregate the plant investors control the demand side of the market. The farmer agents make crop selection decisions based on their individual resources and preferences, and market conditions. Their main resource is the land that they farm, which is spatially specific to account for soil and climate variability, resulting in variation in crop yields. In aggregate the farmer agents control the supply side of the market. A single delivered market price exists for each energy crop, and is adjusted over time based on market conditions. After each time-step agents learn from their own experiences and that of their neighbours, and this influences their future decision-making. Figure 4-1 shows the main agents and their interactions.

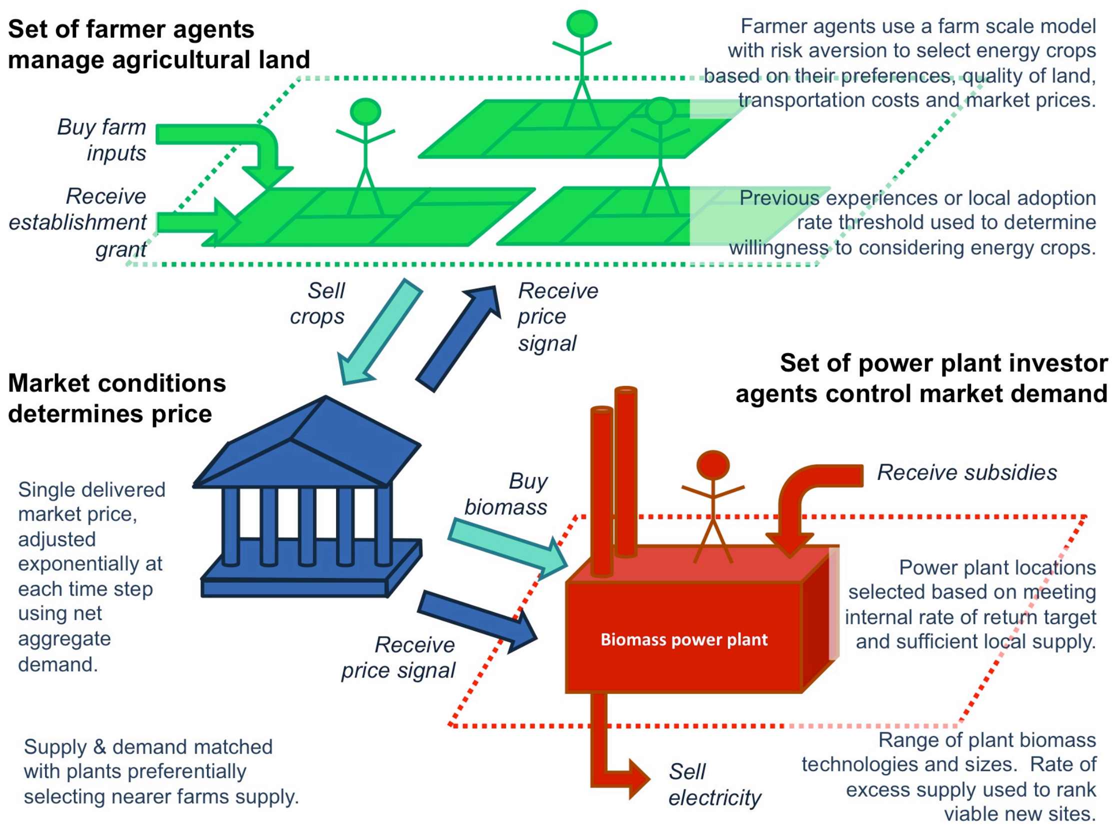


Figure 4-1: Schematic representation of the main agent processes and interactions within the perennial energy crop market model.

The model runs with a time-step of one year, starting in 2010 and continuing until 2050. At each time-step, the following processes take place:

1. Determine location for any potential new plants;
2. Make farmer crop selections;
3. Match supply and demand;
4. Calculate profit and loss of activities;
5. Adjust market price based on market conditions;
6. Apply agents learner.

4.3.1 Plant investor agents

The plant investor agents were assumed to be rational and profit driven, with investment decisions based on achieving a positive net present value of all cash flow discounted at an appropriate rate. This equates to the agent needing to achieve a 'hurdle rate'. The hurdle discount rate is affected by factors including, the market and policy context, cost structure and technology maturity, and so varies between technologies and over time (Oxera Consulting, 2011). The hurdle discount rate differs from the cost of capital, as it also includes factors such as unsystematic risk- and irreversibility (Meier & Tarhan, 2007; Driver & Temple, 2009). Oxera Consulting (2011) conducted an assessment to estimate hurdle discount rates across the UK low carbon electricity generation technologies, and how these rates may evolve over time. Table 4-1 shows the estimates for biomass projects.

Table 4-1: Estimated pre-tax, real discount rate for biomass projects. Data source: Oxera Consulting (2011).

Year	Low estimate	High estimate
2011	9%	13%
2020	8%	11%
2040	6%	8%

To represent variations in investor preferences and perceptions, hurdle rates for each investor agent were determined using a random number from a uniform distribution between the high and low values given in Table 4-1. The interval was interpolated to the required year. All cash flows within the model were real in 2010 terms and pre-tax.

Power plant revenue was generated from the sale of wholesale electricity and Renewable Obligation Certificates (ROCs). The electricity and ROC prices are given exogenously to the model. The ROC price was taken as £37 per ROC, in line with the 2010/11 Ofgem buyout rate (Ofgem, 2012b). A wholesale electricity price of £50 MWh^{-1} was used, as per the DECC (DECC, 2012a) for the same period. The quantity of electricity generated is determined by the biomass supply purchased in that time period (constrained by the plant size), and the efficiency and availability of the plant.

Table 4-2: ROC rates (ROC MWh^{-1}) over time for biomass generation types from the UK Department of Energy and Climate Change 2013 banding review. Data source: Oxera Consulting (2011).

Generation Type	Pre-2015	2015/16	2016/17
Co-firing of biomass, low-range[a]	0.5	0.5	0.5
Co-firing of biomass, mid-range[b]	0.6	0.6	0.6
Co-firing of biomass, high-range[c]	0.9	0.9	0.9
Dedicated Biomass	1.5	1.5	1.4
Dedicated Energy Crops	2	1.9	1.8
Dedicated Biomass with CHP	2	1.9	1.8
Dedicated Energy Crops with CHP	2	1.9	1.8

Notes:

a. <50% of energy provided from biomass sources
b. >=50% and <85% of energy provided from biomass sources
c. >=85% of energy provided from biomass sources

The rate at which ROCs are allocated depends on generation type and fuel; the applicable rates, based on the Renewables Obligation Banding Review 2013-17, are shown in Table 4-2. This includes adjusting some rates downward, to reflect the expectation of lower costs (DECC, 2011c). For electricity generated from dedicated energy crops, the previous rate of 2 ROC MWh^{-1} is maintained for 2013/14 and 2014/15, and subsequently reduced to 1.9 in 2015/16 and then to 1.8 in 2016/17. The initial rate has been maintained for 6 years followed by a 0.1 ROC MWh^{-1} drop in each of the following years. The assumption of the trajectory for ROC rates was that the rate would be decreased by 0.1 ROC MWh^{-1} every two years, starting in 2015, until it reaches 1 ROC MWh^{-1}. The ROC rate is determined using the plant construction date, and held constant for the lifetime of that plant, i.e. it assumes grandfathering rights of ROC payments as per DECC proposals (DECC, 2011c).

All commodity prices, except for energy crops, are fixed during the simulation, and so do not vary either over time, or with the level of supply, i.e. no market elasticity. There are two justifications for this assumption. Firstly, although prices for electricity and other items may be projected to vary over time, so will the other inputs relevant to decision-making. If all prices alter at the same rate there will not be a material impact on model behaviour. Only if a differential in price adjustments exists will a driver for model behaviour occur. Secondly, all the commodities in the modelled system are small components of that commodity's total market. For example, the electricity generated from energy crops is likely to be relatively small compared to the UK electricity generation or demand as a whole, with 350 kha generating approximately 2% of electricity consumption (DECC, 2011d). Although the UK production of agricultural commodities could be affected more significantly, the global nature of these markets suggests that the impact of UK energy crop adoption would be small, with the UK producing around 2% of global wheat production (FAO, 2012).

Plant investor agents evaluate and select the most appropriate plant type from a range of plant technologies and sizes. The current model represents technologies for biomass electricity generation plants. No combined heat and power (CHP), pelletisation plants, or bio-refineries were defined, primarily due to a lack of data on plant capital and operational costs, and the efficiencies of such facilities. Plant type data were derived from the Mott MacDonald (2011) analysis into the costs of low carbon generation, giving a detailed breakdown for three biomass plant technologies. To allow a diverse range of plant sizes to be assessed three sizes of plants were used to for each biomass technology. The sizes were taken as the highest and lowest from that technology size range, plus the base plant size, see Table 4-3. Capital and operating costs reduce over time due to learning, technology advances and increasing economies of scale.

Table 4-3: Installed size and technology types of biomass electricity generation plants modelled.

Technology	Plant size (MW)		
	Small	**Medium**	**Large**
Grate	1	10	30
Bubbling Fluidised Bed	5	40	100
Circulating Fluidised Bed	30	150	300

Fixed operation and maintenance (FOM) costs tend to be linked to the capital costs of the plant. However due to economies of scale, smaller plants of the same type tend to have higher staffing levels and other fixed costs resulting in the smaller plants having relatively higher FOM rates (Mott MacDonald, 2011). Similarly, variable operations and maintenance (VOM) costs are likely to be linked to plant size. Therefore the higher Mot MacDonald FOM and VOM costs were associated with the smaller plants, and the lower figures with the larger plants. Capital cost rates also vary by plant size, as the Mott MacDonald costs are for the central size for each technology, and so these were adjusted by 5% either side of the base plant. The resultant capital, VOM and FOM costs for the 9 types of plants used are shown in Table 4-4.

Table 4-4: Plant data used by technology and size.

Technology	Variable	Unit	Plant Size		
			Small	Medium	Large
Grate	Size	MW	1	10	30
	Capital cost: 2010	£ kW^{-1}	3518	3350	3183
	Fixed costs	Capital cost %	4.5	4.2	3.9
	Variable costs	£ MWh^{-1}	3.4	3	2.7
Bubbling Fluidised Bed	Size	MW	5	40	100
	Capital cost: 2010	£ kW^{-1}	4019	3828	3637
	Fixed costs	Capital cost %	4.6	4.4	4.2
	Variable costs	£ MWh^{-1}	2.7	2.5	2.2
Circulating Fluidised Bed	Size	MW	30	150	300
	Capital cost: 2010	£ kW^{-1}	2287	2178	2069
	Fixed costs	Capital cost %	3.4	3.2	3.0
	Variable costs	£ MWh^{-1}	2.7	2.5	2.2

Learning, technology advances and increasing economies of scale should act to reduce future capital costs. These influences were estimated and combined by Mott MacDonald (2011), into a single future capital cost adjustment factor, as shown in Table 4-5. Interpolating these adjustment factors to the required year and then multiplying by the 2010 capital cost for the required technology was done to obtain the modelled capital costs. No extrapolation for years outside of the range was used, i.e. capital costs were taken as constant after 2040.

Table 4-5: Biomass plant capital cost adjustment factor and efficiencies by technology type. Data source: Mott MacDonald (2011).

Variable	Unit	Grate	Bubbling Fluidised Bed	Circulating Fluidised Bed
Capital cost: 2020	% of 2010 cost	87	84	84
Capital cost: 2040	% of 2010 cost	76	73	74
Efficiency: power	%	31	36	36

The efficiency of power plants to convert biomass feedstock into electricity also varies by technology; the estimates of efficiency used are shown in Table 4-5. The power plant availability, the percentage of time it produces electricity, was taken as 90%, and the operational life as 25 years, for all technologies and sizes (Mott MacDonald, 2011).

At each time-step an attempt is made to find suitable sites for the construction of new power plants. A number of sites (by default 100) are selected at random, and each is assessed for all power plant types and sizes. To evaluate the viability of a specific site, j, and power plant type, k, the maximum economic energy crop purchase price ($p_{j,k,max}$) is calculated to reach the agent's hurdle rate. If this is less than the current market price the site is rejected. The next test is to determine if a site is likely to be able to obtain sufficient supply. This requires a delivered price for potential supply evaluation $\mathrm{p}_{\mathrm{j,k,eval}}$ to be assumed, selected to be equal to $p_{j,k,max}$. Farmers within the economic supply radius are asked to determine their additional potential supply at that delivered biomass price. The default supply radius was taken as 80km. The same value was used by Hellman & Verburg (2011) and is consistent with the findings of maximum supply radii in other studies (Dunnett *et al.*, 2008; Johnson, 2008; Asikainen *et al.*, 2012). Initially, each site evaluation proceeds independently, and does not consider the impact of other sites that may be built in the same time period, although supplies made in the previous time-step to already operating plants are taken into account.

The aggregate potential supply, $S_{j,k}$, for site j, plant type k, and a delivered biomass price of $p_{j,k,eval}$, is given by:

$$S_{j,k} = \sum_{i=n} f_{i,j}\,(p_{j,k,eval}) \qquad \textit{(4-1)}$$

where $f_{i,j}(p)$ is the additional supply at farm i from n possible supplying farms to plant location j, given energy crop price p. If $S_{j,k}$ is greater than the annual biomass energy demand, D_k, to operate plant type k at maximum availability, that plant type is considered viable for that site. If not, the site is rejected for that plant agent.

Normalised maximum excess supply ($e_{j,k}$) is given by:

$$e_{j,k} = (S_{j,k} - D_k)/D_k \qquad \textit{(4-2)}$$

Once all the sites in that time period have been evaluated, the plant agents have selected sites that meet their criteria. To determine at which of the viable sites a plant is constructed, they are ranked by maximum energy crop purchase price ($p_{j,k,max}$), and then excess supply rate ($e_{j,k}$). A plant is constructed at the 'best' site given these criteria and the supply area around it estimated using the over-supply rates, assuming supply is evenly distributed. The remaining viable sites, if any, are re-evaluated, assuming no supply will be available from farms in that area. If after this re-evaluation other sites are still viable the same ranking and selection is repeated. This continues until no more viable power plant sites can be identified.

The random selection of a number of sites could be considered to represent the availability of potential new sites coming onto the market, with all sites being evaluated for a range of plant technologies and sizes. This evaluation attempts to achieve two goals. Firstly, to rank projects based on their financial viability; and secondly, to ensure that sufficient supply exists. The maximum economic energy crop purchase price ($p_{j,k,max}$) gives a proxy for the potential unit profitability of the plant. Due to the economies of scale embodied in the plant type data (see

Table 4-4 and Table 4-5) the larger plant sizes will always have a higher $p_{j,k,max}$ within a given technology, assuming the same hurdle rate. Giving preference to plant and sites combinations with higher $p_{j,k,max}$ figures gives a similar result to basing the allocation on the highest bidder for a site, if an auction or similar process were conducted. Using the rate of excess supply represents the desire of investors to reduce the risk associated with not obtaining sufficient supply.

In the time after a plant becomes operational, the plant investor agents must decide whether to keep the plant open or to close it, if it has become unprofitable. They do this by determining a cumulative net margin. If this margin shows a cumulative loss exceeding 20% of the initial capital cost of the plant then the plant ceases to operate. Once a plant agent closes a plant it no longer takes part in the simulation. No other feedback is implemented on the demand side. All operational plants attempt to obtain supply to allow operation up to the maximum plant availability. The current delivered market price is paid for all supplies purchased.

4.3.2 Farmer agents

Farmer agents decide on the mix of crops to select. They do this in two ways within the model. Firstly, when plants are evaluated for feasibility farmers quote to potential investors the level of energy crop supply they would be willing to provide to a particular location at a specified delivered price. During the evaluation phase they provide a decision for multiple plant locations and delivered prices. Secondly, once within the year, farmers select the mix of crops to grow.

Farmer agents each have a fixed spatial location. The location determines the quality of land, topography and climate, which impact on the potential yields for all the modelled agricultural activities. These variations imply that the optimal crop selection is different at each location. Farmer preferences also differ and this affects the crop selection. Past experience, and observation of a neighbouring farmers decision and the outcomes of these influence preferences and behaviour. Communication between individuals has been shown to be important in the uptake of novel technologies, resulting in the diffusion of knowledge and innovation within a social group (Hägerstrand, 1965; Rogers, 1995).

A two-stage approach was used to model farmer decisions that combined a diffusion of innovation process for the adoption of energy crops with a farm-scale economic model. In stage one the “willingness to consider” (Shafiei *et al.*, 2012) is determined. If farmers have previous experience they use this to inform future behaviour. Where a farmer has no previous experience, the local rate of adoption is used to determine if they are willing to consider energy crops. If they are, then the second stage is to apply a farm-scale model that evaluates the economically optimal area of these crops. This two stage approach is similar to that used in other agricultural land use ABMs (Berger, 2001). More details of each element are given below.

When initialising the model, farmers are assumed to have no direct experience of producing energy crops. However by commencing to grow energy crops they will gain experience and develop an opinion from perceived successes or failures, which informs both their future behaviour and influences their neighbours. At each time-step farmer agents review the outcomes of their energy crop production and update their opinion. They calculate the gross margin obtained up to that time-step from growing the energy crops; costs are calculated as the number of years since establishment at an annual equivalent value (AEV), as in the farm-scale model (Alexander & Moran, 2013). If the gross margin is less than an opportunity cost, the crop is removed and the farmer’s opinion of energy crops becomes negative. An opportunity cost of £150 ha^{-1} was chosen, representing an estimate of land rent (Bauen *et al.*, 2010). However, if the crop produces a greater return the farmer opinion becomes positive. Farmer agents can have therefore one of three views about energy crops: no opinion (as they have no previous experience of the crop), a positive opinion or a negative opinion. A farmer agent with a negative opinion of energy crops will not consider energy crops again. Conversely, farmers with a positive view will check the market conditions when deciding whether to increase the production area of energy crops.

A consistent finding over many studies is that the cumulative adoption of knowledge over time is S-shaped (Rogers, 1995). The number of individuals who adopt at a given time is a function of the current number of adopters in their neighbourhood

(Namatame *et al.*, 2009). Neighbourhoods may be based on physical proximity, or through social or institutional relationships. Differences can occur between individuals in terms of the degree of "resistance" to change (Casetti, 1965), and some potential adopters may respond differently to different sources of innovation (Hägerstrand, 1965). Several approaches to modelling these processes have been proposed (Kiesling *et al.*, 2011). Here an adoption threshold approach was implemented, where a farmer is regarded as willing to consider adoption, if the proportion of neighbours with a net positive experience of adoption is greater than their adoption threshold (Kiesling *et al.*, 2011). Farmer agents are initially assigned an adoption threshold from a normal distribution (Alkemade & Castaldi, 2005).

Model runs were conducted using two distributions of adoption thresholds, both with a mean of 20% adoption. In the default case the standard deviation was chosen so that initially 2.5% of the farmer population, as per the innovators category (Rogers, 1995), would be willing to consider adoption. The second case used a higher initial willingness of 25%, to generate a lower initial restriction on rate of adoption. The standard deviations used were respectively 10.20% and 29.65%, Figure 4-2 shows these distributions of farmer adoption thresholds.

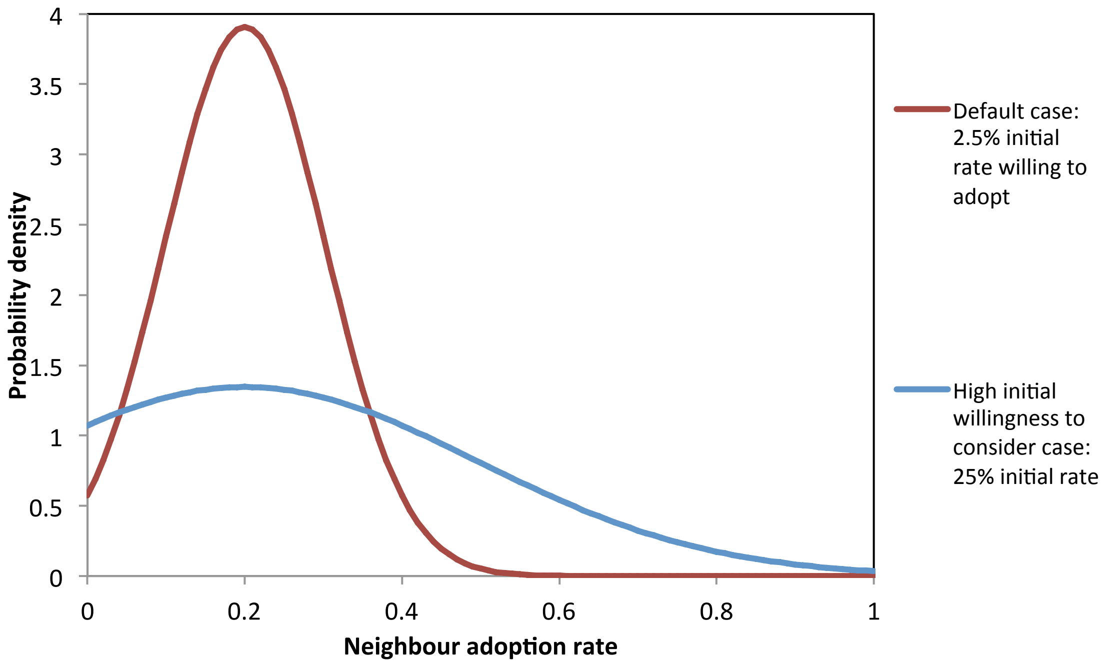


Figure 4-2: Distributions of farmer adoption thresholds, by neighbour adoption rate, for two diffusion scenarios.

The local adoption rate was determined for each farmer agent, using the neighbourhood of network of all farms within a specified radius. The radius was selected for each farmer agent from a uniform distribution between 5km and 20km. The adoption rate was the net proportion of positive minus negative experiences of energy crops for these neighbouring farmers.

Once a farmer agent has been determined to be willing to consider energy crops a farm-scale model is used to make an optimal economic crop selection. The approach and data detailed in chapter 3 were used for the construction of these farm-scale mathematical programmes, which optimise for profit maximisation with constant absolute risk-aversion. Farm agents have risk-aversion assigned from a uniform distribution, between 0.5 and 1.5. For each year and location the yields for all commodities are required. To determine the various crop yields, the model is provided exogenously with maps of crop yields for each of the 11 activities that exist within the model (Alexander *et al.*, 2014a). This provides yields at 2010, 2020, 2030 and 2050 under high, medium and low emissions scenarios from the UKCP09 climate change scenarios (Murphy *et al.*, 2009). Yields for intermediate years were calculated using linear interpolation. The medium emissions scenario was used by default. Social-environmental reasons make some areas unsuitable for energy crop production and these areas were identified from the constraint maps (Lovett *et al.*, 2014). The demand constraints (Wang *et al.*, 2014) were not applied, as demand is endogenously represented within the ABM.

Over the 40-year period modelled there will be changes in the individuals managing farms. As farmers have heterogeneous preferences, for adoption threshold, neighbourhood network distance and risk-aversion, these alter with farm successions. To represent this, at each time-step, the data for a proportion of farmer agents' were reinitialised and preferences reassigned, using the original allocation approach. A 5% probability of a farm succession was assumed, giving 20-year average farm management tenure, in line with data on farm succession and retirement (Lobley *et al.*, 2010).

4.3.3 Supply and demand matching

The level and location of energy crop demand is available from the set of operating plants and supply from the set of farmer agents. However supply and demand must be matched, to allow calculation of the transportation costs, to know how much supply a plant has been allocated, or to identify farms which have unused supply. To match supply and demand, farmer agents were selected at random; each choosing to supply the nearest plant with demand, to minimise transportation costs. This selection process continued until all demand was met or all supply was allocated. If the market is in over-supply, farmers who have unallocated biomass hold this for potential allocation at a future time period. Alternatively when the market is in under-supply, power plants with unfulfilled demand operate at less than maximum capacity. This reduces their profitability, which is reviewed by the agent's learning mechanisms.

4.3.4 Market price

A single global delivered market price (p_t) for energy crops exists at each time period, t, with exponential adjustment based on market conditions(Ghoulmie *et al.*, 2005). The initial value is provided exogenously, but subsequently market prices are adjusted as:

$$p_t = p_{t-1}\, e^{\frac{z_{t-1}}{\lambda}} \tag{4-3}$$

where z_{t-1} is the excess demand normalised by the number of market participants at time t-1, and λ is the model parameter controlling the rate of market adjustment to market signals. z_t is given by

$$z_t = \frac{D_{t,total} - S_{t,total}}{D_{t,total}} \tag{4-4}$$

where $D_{t,total}$ is the total required energy crop demand in the market at time t, and $S_{t,total}$ is the total energy crop supply. The market adjustment parameter, λ, was calibrated to 0.3, see validation section for details. The relationship between Miscanthus and SRC willow prices was maintained using the low heating value (LHV) to provide a consistent price for biomass energy. LHV, also known as net calorific value, is the energy released on combustion after the water contained in the fuel has been vaporised. Miscanthus was assumed to have a moisture content of 15% and an LHV of 15.1GJ oven-dried tonnes $(odt)^{-1}$, while the SRC willow was taken as having 30% moisture, after a period of natural drying, with a 12.1 GJ odt^{-1} LHV (Hillier *et al.*, 2009). The initial market prices were £60 odt^{-1} and £48 odt^{-1} for Miscanthus and short-rotation coppice willow respectively, believed to be close to the current market values (Alexander & Moran, 2013), and a consistent net caloric value for biomass energy of £3.97 GJ^{-1}.

Energy crop farm gate prices were calculated by subtracting the cost of transport between the farm and the power plant from the delivered market price. Farm gate prices therefore vary based on the actual location of supply and demand. This approach implies that farmers meet the entire cost of transport. The calculation of transport costs was based on Bauen et al. (2010), including a 1.6 simple tortuosity factor to straight-line distances and costs shown in Table 4-6. When making annual crop selection decisions, the power plant where the produced biomass will be delivered is not known. In this case delivered energy crop price is adjusted for transport costs, assuming delivery will be to the nearest operating plant.

Table 4-6: Transport cost model data. Data source: Bauen et al. (2010).

Variable	Miscanthus	SRC willow
Fixed transport cost (£ odt^{-1})	4.28	1.81
Variable transport cost (£ odt^{-1} km^{-1})	0.27	0.17

4.3.5 Technical implementation details

The model is implement as a Java programme using the Java Development Kit 7 (Oracle, 2012). The model runs start by first reading in the various input crop yield distributions, primarily as ASCII formatted geographic information system (GIS) files. All farm agents are then created using the random assignment of preferences (see 4.3.2, page 88), the main loop for the model then starts (see 4.3, page 79).

The process of determining farmers' crop selection requires the running of large numbers of farm-scale model cases (Alexander & Moran, 2013), each of which represents a case of crop yields, price and preferences. To minimise the number of cases that need the relatively expensive optimisation step only new unique ones are optimised. A cache of previously calculated crop selections, keyed by all the farm-scale model parameters, is used. If no entry is found for that set of parameters then the case is added to a set for optimisation. The resulting set of new cases is also manipulated to remove any with a duplicate set of farm-scale model parameter values. The new unique cases are used to configure GAMS (Brooke *et al.*, 2010) models for each of these cases. These are executed in batches, with the number of batches is tuned to make use of the compute core available of the machine, on which the model is being run. The outputs of these GAMS optimisations and the previously cached data are then associated with all the relevant agents to obtain a complete representation of the set of agents' behaviour at that time-step.

The complexity of the model and the large number of optimisation problems means the model requires significant compute resource. The results presented are from runs on the Edinburgh Compute and Data Facility Linux compute cluster (Richards & Baker, 2008). Each model run is submitted to the grid engine for allocation, and is configured to run on a single node to allow the parallelisation across cores for the GAMS optimisations. A single run using the default parameters typically takes around 8 to 12 hours to complete. However as many runs are required to get a results distribution and more than one scenario is used the total time is increased. Therefore the number of scenarios and iterations for each is limited by access to sufficient computational resource. As a result, 12 runs were conducted for every scenario presented in this chapter.

4.4 Verification and validation

The validation of ABMs is recognised to be challenging (Happe, 2004; Batty & Torrens, 2005; Ghoulmie *et al.*, 2005; Zimmermann *et al.*, 2009; Knoeri *et al.*, 2011). Several different forms of validation were used here to gain confidence in the model design, implementation and setup. Both individual components and simplified model configuration were tested, as well as comparison on empirical data from oilseed rape adoption.

4.4.1 Simplified model configurations

The model was configured so that the expected behaviour could be predicted, and checked against modelled behaviour. Although these cases were necessarily relatively simple, providing few new insights, they do provide a level of verification, i.e. confidence that the model has been implemented as intended. They also give some limited validation, i.e. checks on the type of behaviour that has been specified through the choice of modelling assumptions and data.

The simplest setup was to constrain the model to a single feasible plant site and type, and to disable both the agent learning and the diffusion of innovation components. The removal of agent learning implies that if a farmer selects an energy crop and discovers that it is not profitable and thus removes it, they will not learn from this experience. Therefore subsequent crop selection will be no different to the choices made prior to the unsuccessful experience. The disabling of the diffusion of innovation is accomplished by setting the probability of selection to 1 for a randomly chosen set of farmers, the innovators, and to 0 for all other categories. When combined with disabling the agent learning, the set of farmers available for energy crop selection remains constant, as farmers cannot change their preferences based on their own or their neighbours' experiences. Given this setup, the model behaviour is controlled by the market price adjustment module and the elasticity of supply from the randomly chosen innovator farmers, with the biomass market price attempting to converge to an equilibrium level. The price may oscillate around the equilibrium level depending on whether the market price adjustment parameter, λ, determines the system to be over or under damped. This occurs regardless of whether the initial price gives a market in over or under supply. The equilibrium price is a function of the profitability of the energy crops in comparison to the other crops, the number of farms within the delivery distance willing to supply, their yields and the plant demand; i.e. most of the inputs except the market sensitivity and the initial price. A default value of λ=0.3 was chosen to produce an under-damped system that reaches equilibrium.

In a further test, the learning module was re-enabled, so that the system's final state becomes sensitive to the initial conditions. After the first time-step the market can either be in over or under supply. If over-supply occurs then at the next time-step farmers with unallocated supply have no market for their production and exit the market. The price is adjusted based on the over-supply amount and then remains fixed, as supply meets demand. This price is not the equilibrium price, but a level determined by the initial state. If the market is in under-supply, the same path is followed as with the non-learning condition, unless the equilibrium price is exceeded. If the equilibrium price is exceeded then the same behaviour as with over-supply occurs, so that the excess supply is not selected and the market price becomes fixed, as supply and demand are in balance.

Similarly, further tests were conducted to explore gradually more complex configurations; for example, with diffusion of innovation and multiple plants.

4.4.2 Component testing

Tests were conducted on the expected behaviour of individual model components run in isolation using a unit-testing framework, JUnit (Beck *et al.*, 2013). Components tested in this way included; plant technology data, ROC rate calculations, individual farm crop selection, and farm level allocation and storage of excess production. The behaviour of other model components was validated within the operation of the model as a whole. This was done using output to recalculate other intermediate values within a spreadsheet and checking them against model output. Model components tested in this manner included the market price adjustments, the unsold energy crops available for future supply at a proposed site, and profitability calculations for farmer and investor agents.

4.4.3 Comparison to empirical oilseed rape data

In addition, to validate the behaviour of the model as a whole the results were compared against empirical data for the expansion of oilseed rape in the UK from the 1970s. The price of oilseed rape stabilised and increased when the UK entered the European Economic Community in 1973 due to the intervention price structure; this heralded the start of a substantial rise in the crop area grown (Wrathall, 1978; Lane, 1983). Although oilseed rape was first introduced in the 19th century, by the 1960s it was not a significant crop and grown mainly in the south and central England. The rapid expansion of oilseed rape in the 1970s and 80s is characterised by a geographical spread from these existing areas, indicating that the spread may have been governed by a diffusion of innovation process (Lane, 1983; Allanson, 1994). As such, oilseed rape appears to provide an analogous case for the farmer adoption of a novel crop in the UK, allowing comparison with the modelled behaviour for energy crops.

4.4.4 Sufficiency of verification and validation

Although a range of approaches have been attempted to verify and validate the model, as outlined above, the question remains whether these are sufficient to consider the model successfully validated. A range of assumptions have been involved in the development and parameterisation of the model, as is typical with

ABMs (Knoeri *et al.,* 2011). However, validation of the model behaviour against empirical data for the energy crop market is not possible, to due a lack of available such data. The component testing and validation against historical data from an analogous case of oilseed rape does provide some confidence. Nonetheless, without the ability to fully validate against observed data for the system being studied, doubt must inevitably remain whether the model's behaviour reflects that of the real system. As a result, some caution should be used when interpreting the results.

4.5 Results

Figure 4-3 shows the modelled area of energy crops (using the central assumptions) and the observed area of oilseed rape in England and Wales for the period 1969-1997. The baseline years were selected in order to overlay the two curves. Similarly, the area axes are on different scales, as eventual market penetration will be different for these crops.

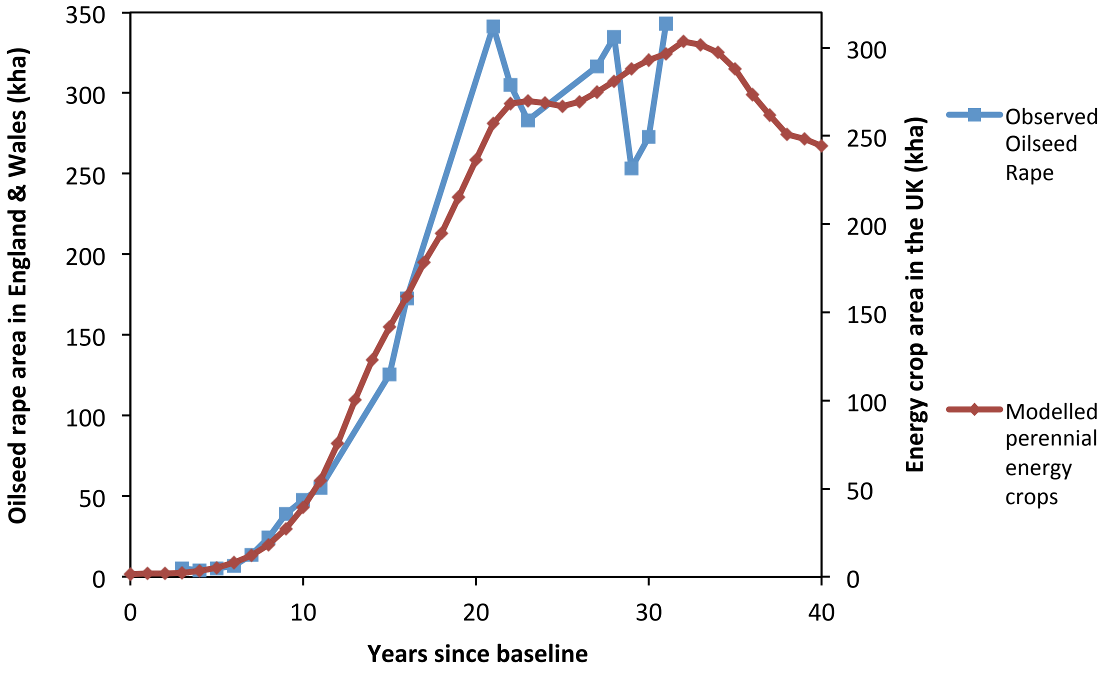
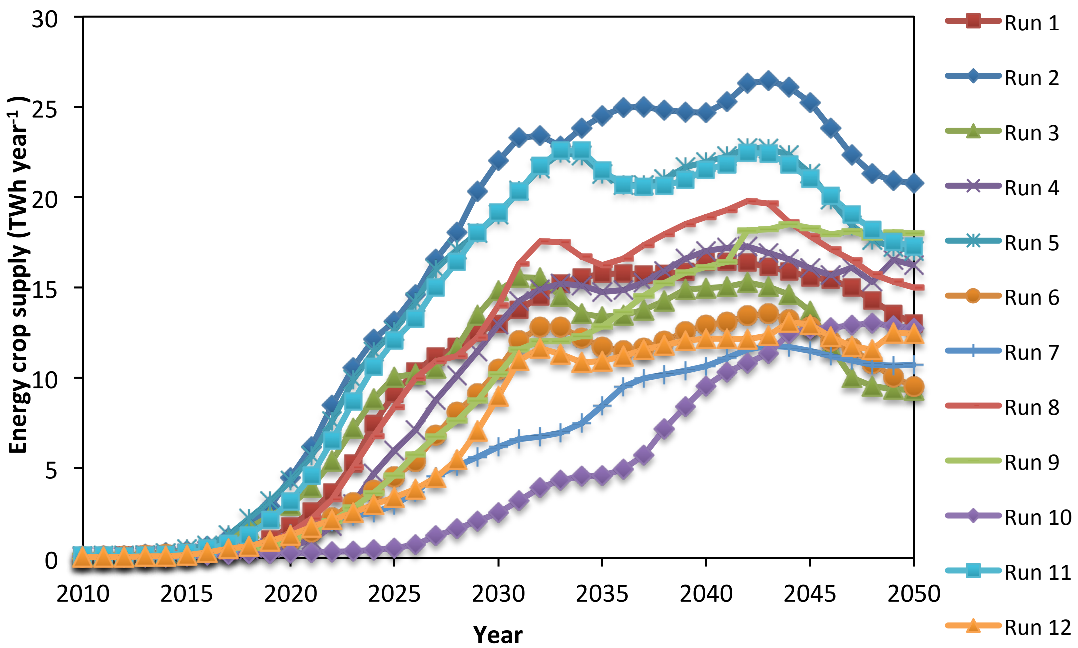


Figure 4-3: Historic oilseed rape data for England and Wales (Wrathall, 1978; Allanson, 1994; EDINA, 2012), against a baseline year of 1966, and mean modelled perennial energy crop areas, using a baseline year of 2010.

Figure 4-3 supports the view that the rate of adoption of both crops follows a typical S-shaped, adoption curve (Rogers, 1995), and that both processes occur over a similar period of time. Data for oilseed rape after this point are difficult to compare as England and Wales subsequently report agricultural statistics separately, with no oilseed rape area data for Wales. Clearly, there are significant differences between these crops, as well as the data being 50 years apart, but the comparison builds confidence in the ability of the model to reflect communication and perceptions of farmers in relation to novel crops. If the diffusion process is a key determinant of the rate of adoption, then the fit of the model's results with the empirical oilseed rape data supports the argument that this behaviour is plausible.

(a)



(b)

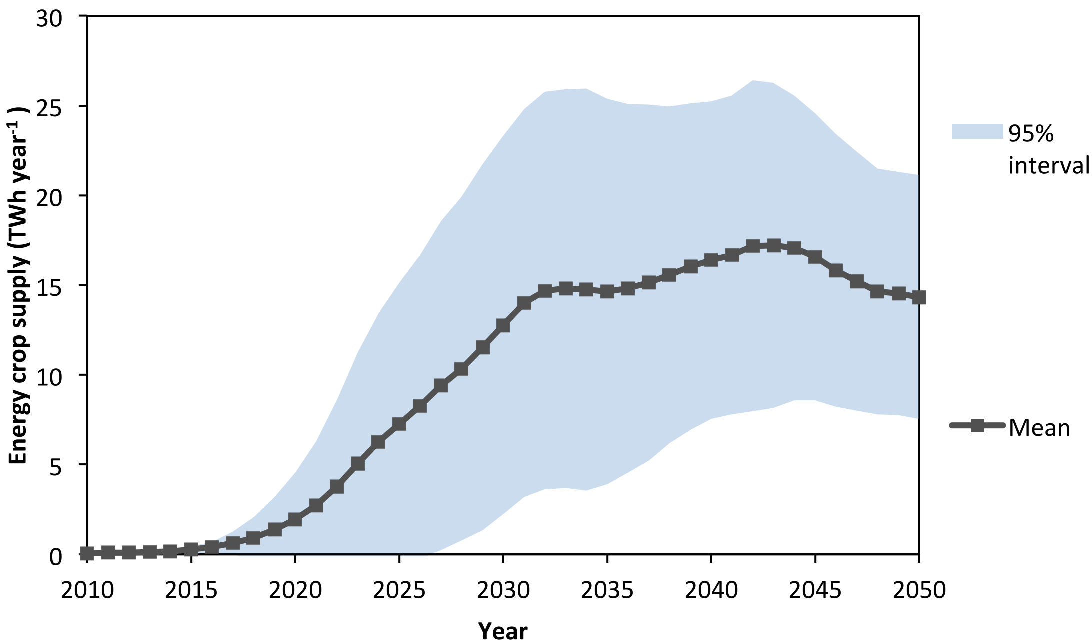


Figure 4-4: Energy crop supply in biomass energy terms over time, a) showing the individual 12 model runs, and b) the mean and 95% internal for these runs.

The model is stochastic due to the probabilistic representation of, for example, the selection of potential sites, investors' hurdle discount rate and farmers' resistance to adoption. Therefore each time the model is run, even with the same set of parameters, a different set of model results emerge. To gain insight into the distribution of possible outcomes, multiple runs are needed for a single set of parameters. Figure 4-4 indicates the distribution of energy crop supply over 12 runs of the model with default parameters. The 95% interval assumes that the results for each year are normally distributed.

The 95% interval of energy crop supply results is wide relative to the mean level (Figure 4-4), which is in part due to a path dependence, or hysteresis, displayed in the model behaviour. The path dependence arises from the reinforcement of the location of plant construction and energy crop selection, based on the locations of the previous plants and energy crops. Once a plant has been built in a location, and a number of farmers have adopted to produce supply for that plant, that area is more likely to be selected for further plant development, and associated energy crop growth. The existence of farmers already growing energy crops increases the number of farmers who are willing to consider growing them (Figure 4-2). The increased pool of farmers potentially increases the availability of supply, which in turn increases the likelihood that further plants may be located in that proximity. The spatial reinforcement, or agglomeration, means that initial plant locations create an influence on the outcome of the model run as a whole. The next chapter examines this in more detail, showing how for a single scenario, three categories of patterns of market locations emerge (Section 5.4.1 and Figure 5-6). The path-dependence, and clustering of results between runs, increases the standard deviation of the results and therefore the confidence interval shown in Figure 4-4.

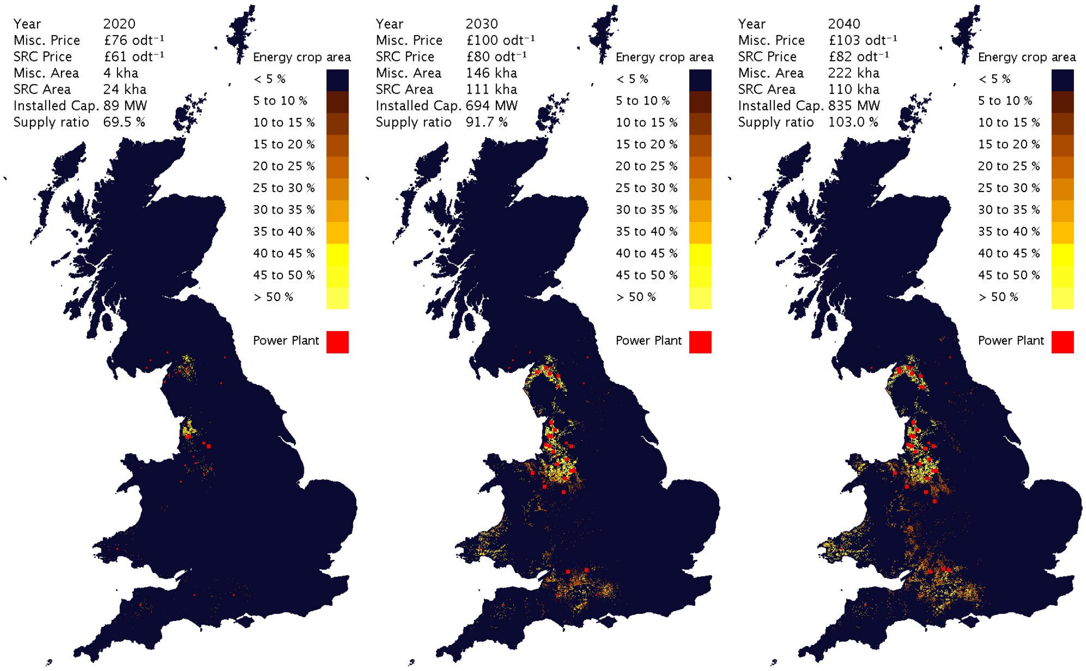


Figure 4-5: Sample output maps of energy crop selection and power plant locations in 2020, 2030 and 2040.

Figure 4-5 shows data from a single default parameter model run, labelled run 1 in Figure 4-4. Figure 4-5 shows the expansion of the energy crop market, with maps showing the area selected for energy crop growth and the location of power plants. The larger the power plant displayed on the map the larger the facility at that location. The selected plant sizes vary from 1 MW to 30 MW.

In the default case, initially only the smallest power plant type is selected (1 MW grate), however as the market expands the bigger and more efficient plants are selected. Figure 4-6 shows the number of each type of plant operating over time, for the same example case. Although similar numbers of 1 MW and 30 MW plants are constructed, 23 and 27 respectively in these results, the large plants quickly dominate in electricity generation capacity terms. Here the first 30MW plant is built in 2019 and forms just more than half of constructed power plants at that date, by 2025 they form over 90% of the capacity. The larger plants (up to 300 MW) are never chosen in this case, however in runs with a greater market size, for example with higher initial adoption, a more diverse selection of plant types is selected, including the largest plants.

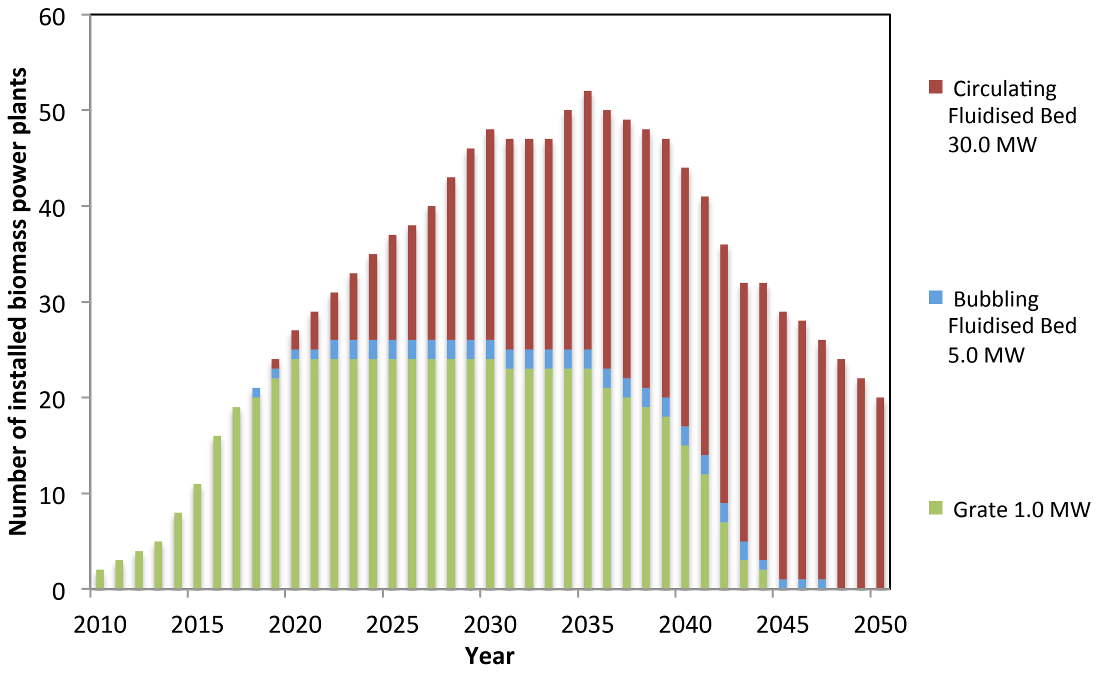


Figure 4-6: Biomass power plants operational for dedicated energy crop production, broken down by plant technology and size, for one sample model run.

The breakdown of energy crop selection shows that SRC willow is selected earlier in the model run, with Miscanthus becoming more important as the market expands and the price increases (Figure 4-7), consistent with previous findings (Alexander *et al.*, 2014a).

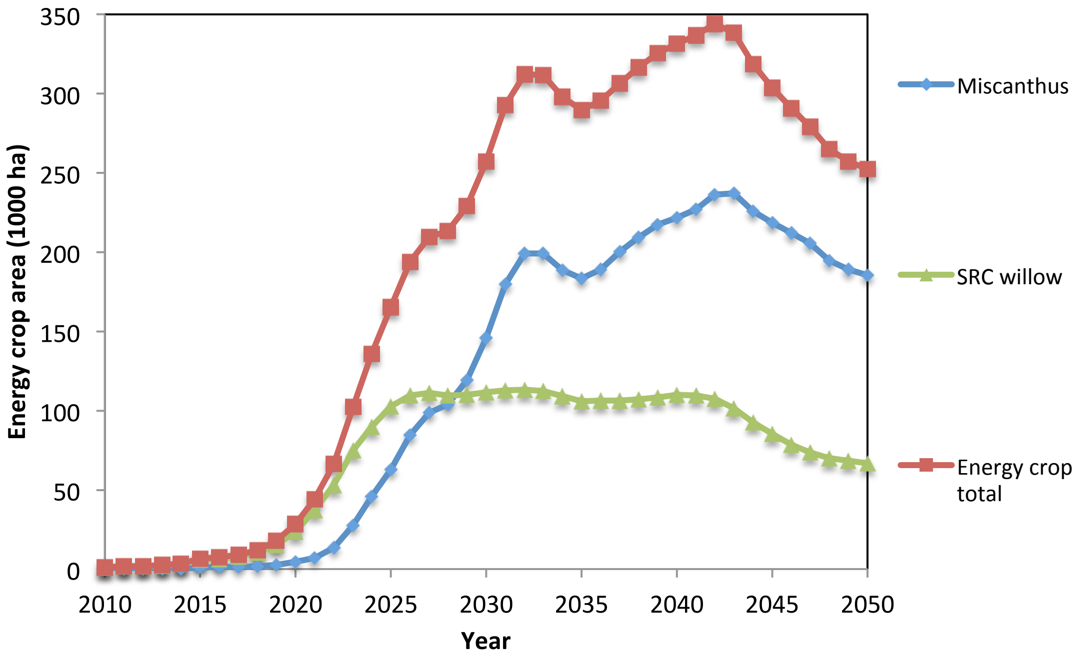


Figure 4-7: Areas of Miscanthus and SRC willow plantations within the UK over time, one sample run.

Although the exact behaviour varies between runs, some common features occur, especially concerning the initial spatial distribution. This is likely to be a result of the relative crop yields, i.e. the initial selection is likely to occur in areas with relatively high energy crop yields in comparison to yields of conventional agricultural activities. Initially, a small area of energy crops is selected in the north west of England. The area cultivated in this region increases over time and spreads geographically outwards. The south west of England also has some energy crop selection, around 2018, which also then consolidates and spreads. A similar spread was seen for the historic oilseed rape expansion, but primarily on the eastern (arable) side of the country (EDINA, 2012).

In the baseline scenario, the market price is initially relatively stable, before rising to fluctuate around £100 odt^{-1} from 2023 for Miscanthus, equivalent to a biomass energy price of £6.6 GJ^{-1}. The relationship between supply and demand and the market price for Miscanthus and SRC willow is shown in Figure 4-8.

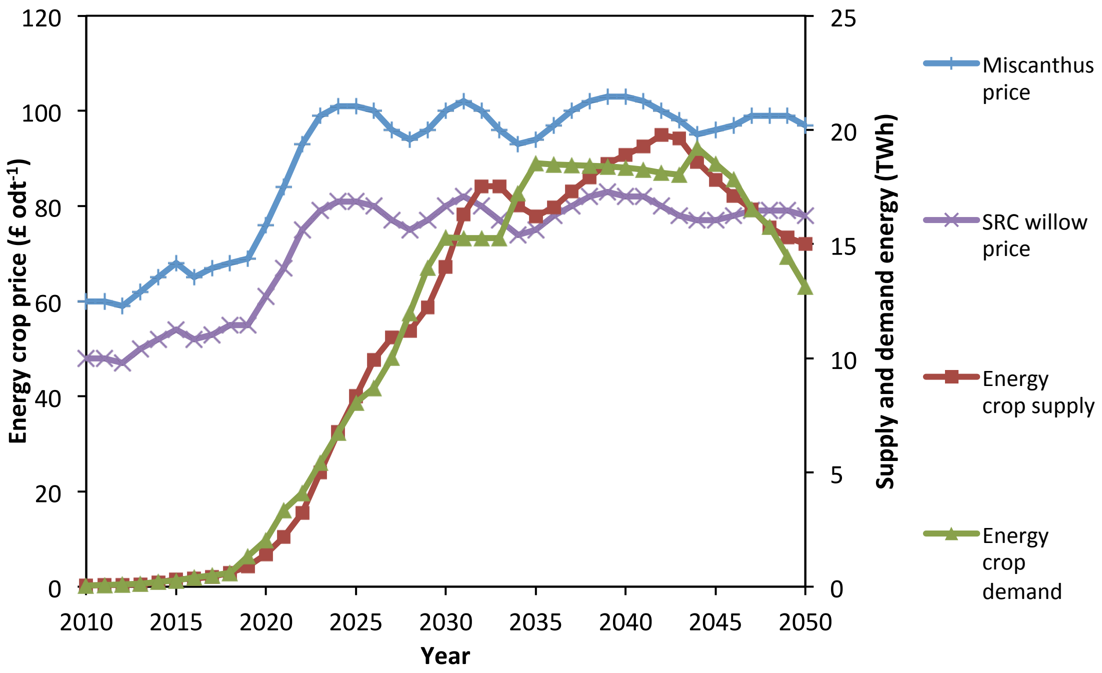


Figure 4-8: Energy crop prices and biomass supply and demand over time from one model run.

The consensus for energy crop resources in the UK has been around 1 to 2 Mha in 2020 and 2030 (Gill *et al.*, 2005; DEFRA, 2007; Aylott *et al.*, 2008; E4tech, 2009; Bauen *et al.*, 2010). The area of energy crops estimated here is smaller. The mean model result for 2020 is 39 kha (0.6% of UK cropland), or 9 times lower than the DEFRA (2007) figure, which already assumes that only 35% of the available resource is utilised. This would be sufficient to provide supply for 130MW of electricity generation capacity. Similarly, in 2030 the modelled area is 236 kha (4% of UK cropland), or 6 and 9 times less than the previous figures (E4tech, 2009; Bauen *et al.*, 2010), and able to support 700MW of electricity generation. The modelled area reaches a maximum in 2041 of 303 kha, before falling back to 244 kha by 2050.

If the diffusion of innovation is changed so that 25% of farmers are initially prepared to consider the crop rather than the 2.5% used in the baseline case, then the rate of adoption within the model is increased. However, the level of adoption achieved is also far greater, with a mean area of 1.8 Mha in 2020 and 1.5 Mha in 2030. Figure 4-9 shows the mean total energy crop area selected for both of these cases, averaged over 12 runs. The 2020 area is greater than previous estimates of available resource for that date, being 80% more than the higher estimate (Gill *et al.*, 2005). Although the 2020 result is apparently significantly higher than the DEFRA (DEFRA, 2007) estimate of 350 kha, this includes a factor of 35% for the available resource, which more closely reflects the figures reported here (Gill *et al.*, 2005; Aylott *et al.*, 2008). The results for 2030 are the same as one previous estimate (Bauen *et al.*, 2010) and broadly similar to another (E4tech, 2009).

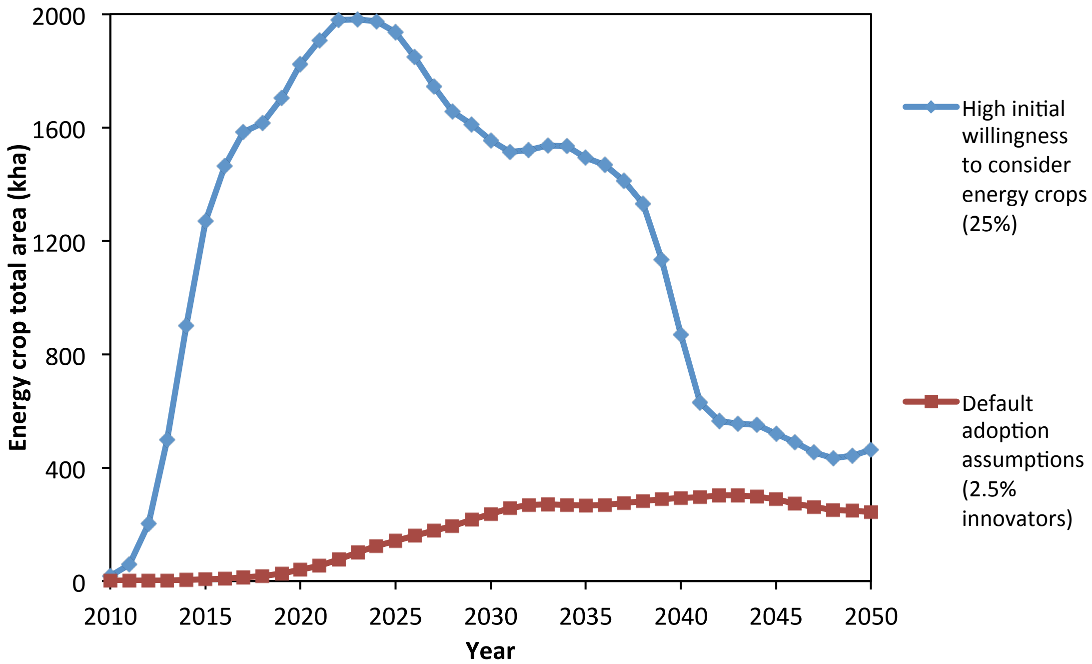


Figure 4-9: Areas of perennial energy crops within the UK over time for the two diffusion assumptions (mean model results of 12 runs).

The 25% innovator rate was not chosen to represent at plausible scenario. Rather, it was designed to test the model's behaviour when farmer diffusion is not a significant factor, and so allows a comparison with existing estimates of energy crop adoption. The proportion of farmers in the UK who could be classified as innovators is expected to be closer to the value of 2.5%, as proposed by Rogers (1995). A sensitivity analysis is conducted in Chapter 5, with a range of 1.25-5%, to attempt to assess the sensitivity to this parameter over a more realistic range.

4.6 Discussion

The importance of the diffusion component can clearly be seen by the change in behaviour when the initial adoption rate is increased (Figure 4-9). It is perhaps unsurprising that the rate of adoption increased, but more interestingly there is a very substantial increase (six fold by 2030) in the level of adoption achieved. Two factors appear to explain this. First, the more rapid adoption allows more plants to be built with the high ROC rates on offer in earlier years. Second, the greater availability of potential supply allows larger and more efficient plants to be built. Both these factors allow higher market prices to be sustained on the demand side, further increasing the potential supply, and reinforcing the effect. The decline in energy crops after 2037 is due to the closure of plants reaching the end of their operational life. Changes in market conditions (reductions in ROC rates, and higher market prices) mean that too few new plants are built to replace the lost capacity. To a lesser extent the same decline is also seen in the baseline case.

The model results suggest that the market for perennial energy crops in the UK may not develop to the size that has been suggested (Gill *et al.*, 2005; DEFRA, 2007; Aylott *et al.*, 2008; E4tech, 2009; Bauen *et al.*, 2010), and that the rate of uptake may initially also be slow (Figure 4-8). There are several reasons to believe this is a plausible result. It is consistent with the low levels of adoption seen to date (Natural_England, 2006; RELU, 2009), most recently evidenced by the small area (1305 ha) receiving establishment grants in the period 2007 to 2011 (Natural_England, 2011), despite the existence of 50% grants throughout the period (Natural_England, 2009). Also, when the adoption assumptions are relaxed, to reduce the implied diffusion restriction, the resulting areas selected come broadly into line with previous estimates. The ability of the model to match results of previous studies using the higher initial adoption rate is encouraging, as none of these studies explicitly represented the adoption behaviour of farmers and interactions between them (Gill *et al.*, 2005; DEFRA, 2007; Aylott *et al.*, 2008; E4tech, 2009; Bauen *et al.*, 2010). Hence, when this element is suppressed, by increasing the initial adoption rate, the model more closely matches the assumptions from previous studies. Finally, the adoption rate in the baseline case is consistent with the previous uptake of a novel crop, using the expansion of oilseed rape from the 1970s as an analogue.

A number of aspects relating to the potential development of the domestic UK perennial energy crop market are not included within the model. The most significant may be the lack of other sources of biomass, e.g. imported biomass, or domestic supply from agricultural residues, wood and waste. Investor risk to supply would be reduced by siting plants with the ability to source a variety of suitable biomass, for example by being close to a port. There is, however, currently a 0.5 ROC MWh^{-1} premium paid for power produced from dedicated energy crops over other biomass sources, see Table 4-2, which is a substantial incentive to operate with these crops. In addition the cost of transport of these materials is high, leading to plants being sited as close as possible to the location of production. Both of these factors it could be argued justify, at least partially, the exclusion of other biomass sources. Nonetheless, it would be useful to increase the model scope further to include this aspect, as a topic for future work.

No constraints have been place on the availability of planting capacity to establish new energy crop plantation, either due to the level of investment or the local availability of the required equipment. If significant planting capacity constraints exist, they would act to slow adoption and further lower the uptake level, both intensifying the behaviour noted and the conclusions drawn. However, the planting rates in the first 7 years from the default scenario is 1155 ha $year^{-1}$ which less than the 1170 ha $year^{-1}$ rate seen under the Energy Crop Scheme (Natural_England, 2006). Therefore we do not believe that planting capacity forms a significant constraint, as initial rates seen in the model have been shown to be achievable, and planting capacity could be increased over this period to meet the higher establishment rates that the model suggests for subsequent years.

Other sources of demand for biomass also exist that have not been represented here, for example coal power stations have demand for biomass for co-firing. The co-firing of any biomass, with up to 50% of energy provided from biomass sources, receives 0.5 ROC/MWh while dedicated energy crop electricity generation receives

2.0 ROC/MWh (Ofgem, 2013b). The higher dedicated energy crop subsidy allows support of a relatively high energy crop market price. As a consequence it only appeared economic to use this form of biomass for co-firing when the modelled biomass price dropped from the initial value, a situation not seen in using the scenarios presented here. The implication is that energy crop resources are better allocated to dedicated biomass plants. However, co-firing could provide a stimulus to the energy crop market development given alternative subsidy levels, and this is an area where further research into the impact of alternative policy frameworks, including a representation of co-firing would be appropriate. Other plant types such as CHP, pelletisation and other biomass facilities that could consume energy crops were not included either. The main reason was a lack of data to parameterise the construction and operation of such facilities. For example CHP costs are very site specific depending on the intended use for the heat. The ABM approach would provide support for integration of such facilities into the model, if data were available to characterise them.

4.7 Conclusions

The inclusion of the contingent interaction between farmers and power plant investors suggests a figure for the area of UK perennial energy crops that is between 6 and 9 times lower than previously published. The main driver for this reduction is the time lag arising from the spatial diffusion of innovation that moderates the rate of farmers' adoption of these energy crops. The adoption pattern and rates produced are consistent with the adoption of oilseed rape from the 1970s, providing a degree of confidence in the model's behaviour. Both the modelled behaviour and the historical analogy indicate that complete adoption of a novel crop can take more than 20 years. In the context of energy crops this means that even with favourable policy support it may take 20 years to achieve an uptake close to the 350 kha identified by DEFRA (2007) for 2020. The model's ability to support an explanation of the trend in empirical data, in terms of a spatial diffusion process, has implications for the need to account for time lags arising from spatial diffusion in modelling land use change or the uptake of other novel crops or technologies, e.g. climate change mitigation or adaption.

There is some uncertainty surrounding the subsidy level until 2017 (DECC, 2011c), and considerably more uncertainty over the longer term. Future work could explore the potential impacts of different policies options. A sensitivity analysis for each parameter in the model would be informative to understand the relative importance of parameters and potentially provide further insights into market behaviour. The results of work to address these objectives are presented in chapter five.

CHAPTER FIVE

COSTS AND POTENTIAL FOR CARBON ABATEMENT

After article: Alexander P, Moran D, Rounsevell M, Hillier J, Smith P (2014b) Cost and potential of carbon abatement from the UK perennial energy crop market. *Global Change Biology Bioenergy*, 6, 156-168. See Appendix IV.

5.1 Abstract

Biomass produced from perennial energy crops is expected to contribute to UK renewable energy targets, reducing the carbon intensity of energy production. The UK Government has had incentive policies in place targeting both farmers and power plant investors to develop this market, but growth has been slower than anticipated. Market expansion requires the interaction of farmers growing these crops, with the construction of biomass power plants or other facilities to consume them. This chapter uses an agent-based model to investigate behaviour of the UK energy crop market and examines the cost of emission abatement that the market might provide. The model is run for various policy scenarios attempting to answer the following questions: Do existing policies for perennial energy crops provide a cost effective mechanism in stimulating the market to achieve emissions abatement? What are the relative benefits of providing incentives to farmers or energy producers? What are the trade-offs between increased or decreased subsidy levels and the rate and level of market uptake, and hence carbon abatement? The results suggest that maintaining the energy crop scheme, which provides farmers' establishment grants, can increase both the emissions abatement potential and cost effectiveness. A minimum carbon equivalent abatement cost is seen in scenarios with intermediate subsidy levels for biomass electricity generators. This suggests that there is an optimum level of support that most cost effectively stimulates the market to achieve emissions reduction.

5.2 Introduction

Biomass could supply 8-11% of the UK's total primary energy demand by 2020 (DfT *et al.*, 2012), and form a significant part of meeting the legally binding target of 15% of its energy consumption from renewable sources (DECC, 2011a). The greatest growth in UK domestic biomass supply is expected to come from agricultural residues and energy crops (DfT *et al.*, 2012). It has been suggested that between 930 and 3630 kha of land in England and Wales could be used for growing dedicated perennial energy crops, Miscanthus and willow or poplar grown as SRC, without impinging on food production (DfT *et al.*, 2012). However, uptake of these crops has been limited; only 11 kha in 2011, with the planting rate dropping to only 0.5 kha year^{-1} from 2008-11 (DEFRA & Government Statistical Service, 2013), with evidence this is driven by farmers behaviour causing a spatial diffusion process (Alexander *et al.*, 2013). Although there is currently no target for areas of these crops, 350 kha by 2020 was suggested in the Biomass Strategy (DEFRA, 2007), but it is now expected that the actual figure will be much lower (Aylott & McDermott, 2012).

Different policies have been available to support the UK energy crop market. Subsidies have been targeted at both the farmers and the energy producers. Farmers in England have had access to grants covering 50% of the establishment costs for planting Miscanthus or SRC (Natural_England, 2009). While renewable electricity generators have been able to receive support under the Renewable Obligation (RO) mechanism (Ofgem, 2013b). The number of Renewable Obligation Certificates electricity generators receive varies based on the amount renewable electricity generated, and a support band determined by technology and commissioning date. These certificates can then be sold (from 2009 to 2012 prices have ranged been between £37 to 40 ROC^{-1} (Ofgem, 2012b)), providing the generator with a premium in addition to the wholesale electricity price. More recently, Renewable Heat Incentives (RHIs) have also been available for the generators of renewable heat. However the existing subsidy arrangements are in flux; the RO scheme ends in 2017, and the energy crops establishment grant closed to new applications at the end of August 2013, although planting of approved areas will continue, potentially until

2015. Electricity Market Reform (EMR) proposals, which are effectively the replacement for RO, have been published (DECC, 2013a). The stated aim of the EMR proposals is to decarbonise energy generation in a cost-effective manner, while maintaining security of supply. It contains three main elements; a feed-in tariff using Contract for Difference (CfD), a carbon price floor, and a capacity market. Under CfD, generators revenues, from electricity and ROCs, is replaced by a single fixed price level known as the 'strike price'. The draft CfD strike prices are claimed to have been set to be consistent with the ROCs, however dedicated biomass would require combined heat and power (CHP) facilities to receive support (DECC, 2013a). It is unclear whether there will be a replacement for the Energy Crop Scheme, or the timing or the form that any replacement might take, but there are calls for a new scheme (Aylott & McDermott, 2012; Lindegaard, 2013).

Biomass energy is sometimes assumed or stated as having zero net emissions of Carbon dioxide (CO_2) (Al-Mansour & Zuwala, 2010; Bertrand, 2013), or given a zero emissions factor (HM Treasury & HM Revenue & Customs, 2010). However, although the carbon released during the energy production has been captured during the growth of the plant, there are direct and indirect sources of potential emissions. Direct emissions relate to the production, transport, handling and processing lifecycle stages, while indirect emission can occur due to land use change potentially causing soil carbon changes. Several assessments of GHG emissions have been undertaken for energy crop production or related generation technologies (Bullard & Metcalfe, 2001; Bauer, 2008; St. Clair *et al.*, 2008; Cherubini & Jungmeier, 2009; Wiltshire & Hughes, 2011; Perilhon *et al.*, 2012). These have typically assumed average values for energy crop yield, transport distance and power plant parameters. In fact these will vary, for example between farms, due to the location of production and consumption, and by the size and type of power plant. Although there is some work including spatially specific crop yields to determine maps of potential emissions (Hillier *et al.*, 2009), no study to date has considered how the behavioural aspects of adoption, such as imitation of behaviour and diffusion of innovation, may impact the resulting emissions, or how this might be impacted by changes in subsidies.

This chapter uses an agent-based model to investigate the UK energy crop market and examines the cost of CO_2 equivalent (CO_2e) abatement that the market could provide. An existing GHG balance assessment (St. Clair *et al.*, 2008) is used as a framework to assess the emissions. The model is run for various policy scenarios, representing possible subsidy trajectories and divisions of support between farmers and energy producers, attempting to answer the following questions: Do existing policies for perennial energy crops provide a cost effective mechanism in stimulating the market to achieve emissions abatement? What are the relative benefits of providing incentives to farmers or energy producers? What are the trade-offs between increased or decreased subsidy levels and the rate and level of market uptake, and hence carbon abatement? A sensitivity analysis is also conducted to determine the behaviour of the system to a range of parameters, the results of which are used to further understand the policy scenario results. The chapter describes the method for calculation of emissions from generating energy crop electricity and emissions avoided from displacement of this electricity from another source. The agent-based model and the scenarios used are then outlined, before the results are presented and discussed.

5.3 Materials and methods

5.3.1 Emissions from energy crop electricity generation

Emissions for each energy crop and associated management were calculated based on initial estimates set out in St. Clair *et al.* (2008), with some modifications. Emissions from the production of the Miscanthus rhizomes, willow cuttings and removal of the crop at the end of its productive life were added. Emissions associated with the production of Miscanthus rhizomes have been estimated as 278.7 kg CO_2e ha^{-1} (Bullard & Metcalfe, 2001). For willow cuttings an estimate of 174.2 kg CO_2e ha^{-1} was used since no specific figure was available and it was assumed emissions proportional to the level of input required to grow the rhizomes and cuttings, as approximated by their respective costs (Turley & Liddle, 2008). Emissions were also added for crop removal; both crops were assumed to require broad-spectrum herbicide and sub-soiling.

Fertiliser application practices were assumed to follow the National Non-Food Crops Centre guidelines (NNFCC, 2010a, 2010b). Miscanthus does not require significant fertiliser application as it recycles nutrients into the rhizome. However at establishment it is recommended to apply 85 kg ha^{-1} N and 45 kg ha^{-1} each of P and K (NNFCC, 2010a). An additional 40 kg ha^{-1} N may also be required and these are assumed to be applied after year 5 and 10. For SRC willow, sewage sludge or manure is recommend at establishment and after each harvest. The use of 100 kg ha^{-1} of N from 0.6% N manure at establishment and after each harvest application was assumed (NNFCC, 2010b). The application of fertiliser creates direct emissions from increased production of nitrous oxide (N_2O) due to the higher levels of N, and indirect emissions from volatilisation, leaching and run-off. Emissions are also caused by the fertilisers' production, transport and application. The direct emissions are estimated to be 1% applied (IPCC, 2006), with lower indirect rates through volatilisation, leaching and run-off. However for inorganic fertilisers the production emissions can be significant (Wood & Cowie, 2004).

The impact of each of the fertiliser regimes was estimated assuming well drained soil, of medium soil organic carbon (between 1.72% and 5.16% soil organic matter), and medium texture, using a farm carbon calculator called Cool Farm Tool (CFT) (Hillier, 2013). CFT was originally created in collaboration between University of Aberdeen, Unilever and the Sustainable Food Lab, and since has been used by range of multinational companies, including Marks & Spencer, PepsiCo and Yara, to assess their agricultural greenhouse gas emissions (Cool Farm Institute, 2014). The emission for Miscanthus was estimated as 915.1 kg CO_2e ha^{-1} at establishment and 518.8 kg CO_2e ha^{-1} in years 5 and 10. For SRC willow, the estimate was 428.9 kg CO_2e ha^{-1} for each manure application (Hillier, 2013).

No account was taken of changes in soil organic carbon; the justification and potential consequences of this assumption are explored in the discussion section. Table 5-1 summarises, for each energy crop, the emission parameters associated with crop production.

Table 5-1: Perennial energy crop production emission parameters. Data sources: St. Clair et al. (2008) and Bullard & Metcalfe (2001).

Operation	**Occurrence**	**Miscanthus ($kg\ CO_2e\ ha^{-1}$)**	**SRC willow ($kg\ CO_2e\ ha^{-1}$)**
Site preparation	At establishment	119.2	70.8
Rhizomes / cuttings	At establishment	278.7	174.2
Planting	At establishment	278.3	251.5
Herbicide / Pesticide	At establishment	35.6	26.8
Fertiliser	See table notes	915.1[a] / 518.8[b]	428.9[c]
Harvesting	At harvest[d]	48.8	57.9
Removal	At end of productive life[e]	63.4	63.4

Notes:

a. Fertiliser applied at Miscanthus establishment.
b. Fertiliser applied at years 5 and 10 for Miscanthus.
c. Fertiliser applied at SRC establishment and after every harvest.
d. Miscanthus harvested annually, and SRC willow harvested every 3 years.
e. 16 and 21 year productive life for Miscanthus and SRC willow respectively.

Handling for on-farm storage and handling for transport loading and unloading where both estimated as 3.29 kg $CO_2e\ t^{-1}$ (Elsayed *et al.*, 2003). Haulage emissions where taken as 0.17574 kg $CO_2e\ t^{-1}\ km^{-1}$, assuming a return trip with an average load returning empty for an articulated carrier >33t (DECC, 2013b). Biomass ash disposal was included in the transport cost assuming 60 kg t^{-1} of fuel is used (Elsayed *et al.*, 2003). As these figures are for mass of material handled and crop yield are in oven dried tonnes (odt), these figures were adjusted to account for moisture contents of 15% for Miscanthus and 30% for SRC willow (Hillier *et al.*, 2009). Storage is calculated using tonnes of fuel produced (t_p), while transportation is calculated using tonnes of fuel supplied (t_s). Where crops are unsold, these figures will differ in a given period.

The CO_2 produced by the combustion in the electricity generation process is not included, as unlike other fuels, it does not increase atmospheric CO_2 since an equivalent amount is captured during crop growth. However methane (CH_4) and N_2O, gases with higher global warming potentials (Forester *et al.*, 2007), are both emitted and need to be included in these calculations. The rate of emission per MWh of feed fuel (MWh_f) were taken as 0.0072 kg CH_4 MWh_f^{-1} and 0.018 kg N_2O MWh_f^{-1} (Elsayed *et al.*, 2003). The construction of a biomass power plant involves significant GHG emissions associated with the production of steel and concrete (Jungmeier *et al.*, 1998). Emissions per MWh of installed plant capacity (MWh_i), was taken as 38.5 kg CO_2 MWh_i (Georgakellos, 2012). These construction emissions are fixed, and once the plant is built will occur whether the plant operates at full capacity or not. Table 5-2 gives a summary of these figures.

To demonstrate how these figures are used to calculate emissions, we use an exemplar of the emissions to produce 1 MWh of electricity (MWh_e). Taking a 12 odt ha^{-1} yield on both crops and a transport distance of 50km, with the same 1.6 tortuosity factor, and a biomass electricity plant with 30% efficiency, gives a total equivalent emissions of 91 kg CO_2e MWh_e^{-1} for Miscanthus and 102 kg CO_2e MWh_e^{-1} for SRC (Figure 5-1). These figures are in-line with previously published figures. Evans *et al.*(2010) reviewed previous assessments of CO_2 equivalent emissions from biomass generation, finding a mean of 62.5 kg CO_2 MWh_e^{-1}, with the highest being 132 kg CO_2 MWh_e^{-1}. The highest figure was for SRC willow power production (Styles & Jones, 2007). These values also lie within the range published in the UK Biomass strategy for SRC chips (DfT *et al.*, 2012).

Table 5-2: Emission parameters by lifecycle stage.

Source	Units	Value
Miscanthus production	kg CO_2e ha^{-1}	219.3[a]
SRC willow production	kg CO_2e ha^{-1}	210.6[a]
Storage	kg CO_2e t_p^{-1}	3.29
Loading / unloading	kg CO_2e t_s^{-1}	3.29
Transport	kg CO_2e km^{-1} t_s^{-1}	0.1863[b]
Power plant construction	kg CO_2e MWh_i^{-1}	38.5
Power plant operation	kg CO_2e MWh_f^{-1}	5.54

Notes:
a. Annualised over crop productive life
b. Including ash return transport

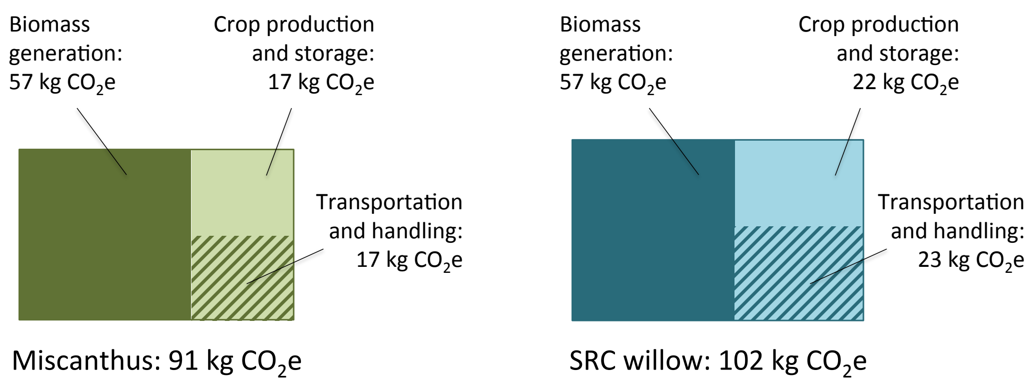


Figure 5-1: CO_2 equivalent emissions for 1MWh of electricity generated from Miscanthus and SRC willow, assuming a yield of 12 odt ha^{-1} and a 50 km transportation distance, area proportional to emissions.

5.3.2 Abated emissions

Electricity generated from perennial energy crops displaces generation from other sources. In 2010, the UK grid emissions were 522 kg CO_2e MWh_e^{-1}, with 457 kg CO_2e MWh_e^{-1} from direct sources and 65 kg CO_2e MWh_e^{-1} from indirect sources, i.e. production and distribution of fuel (AEA, 2012). Using the same indirect emissions, the figures for coal and gas were 951 kg CO_2e MWh_e^{-1} and 400 kg CO_2e MWh_e^{-1}, respectively (DECC, 2013b). Figure 5-2 compares coal, grid and gas CO_2e emissions to the example cases for Miscanthus and SRC willow. Although the displaced source could be considered to change over time and the grid average figure is expected to reduce (DfT *et al.*, 2012), the use of coal has recently increased, now accounting for 39% of the UK's electricity generation in 2012 (DECC, 2013c). Accordingly the analysis was undertaken with both the coal and grid average emission factors.

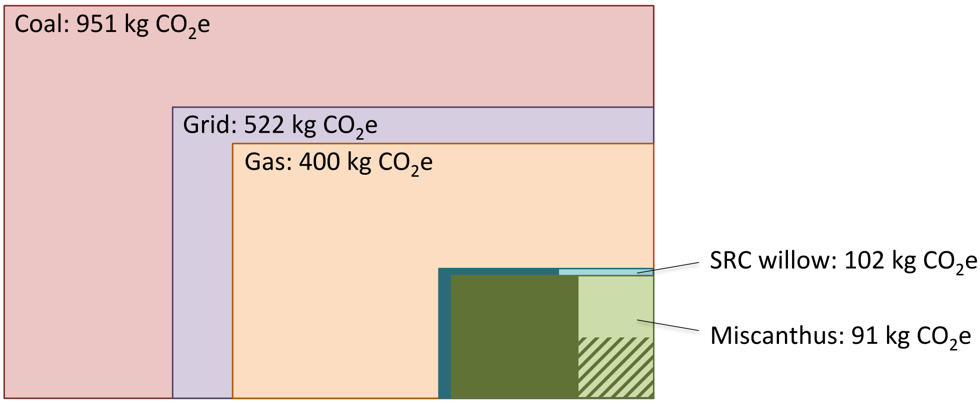


Figure 5-2: Total (direct and indirect) emissions, as CO_2 equivalent, to generate 1MWh of electricity in the UK from various fuels (AEA, 2012; DECC, 2013b). Areas are proportional to emissions and sources overlaid, with the lower emissions fuels towards the top.

5.3.3 Agent-based model

An ABM of the perennial energy crop market (Alexander *et al.*, 2013) was used to simulate the market development under various scenarios. ABM allows the dynamic representation of decision-makers and their interactions, with the system behaviour emerging through agent interactions with one another and their environment (Rounsevell *et al.*, 2012). The approach was selected as an ABM allows the spatial and dynamic behaviour of complex systems to be investigated (Zimmermann *et al.*, 2009), and supports the two-way interaction between micro and macro scales (Happe, 2004), features which many other approaches find intractable.

A summary of the construction and workings of the model used are described here, full description is available in Chapter Four. The model has a set of farmer agents and a set of power plant investor agents (see Figure 4-1, page 80). Farmers each manage a 1km^2 (100 ha) parcel of agricultural land, making crop selection decisions based on their resources (including spatially specific crop yields (Tallis *et al.*, 2012; Hastings *et al.*, 2014)), individual preferences and market conditions. Each farmer first applies a behavioural test to determine whether they are willing to consider adoption, before applying a farm-scale economic model with risk-aversion, to determine an optimum crop selection given their spatial resources and initially randomly allocated preferences (Alexander & Moran, 2013).

Farmers' willingness to consider adoption is determined by drawing on their own previous experience, or where there have none, by looking at the local level of adoption in their neighbour farms. Farmers are taken as willing to consider energy crops if the proportion of successful local adoption is greater than their threshold value, which is randomly assigned from a normal distribution. The initial rate of adoption, or proportion of innovators (Rogers, 1995), is the fraction of farmers willing to consider adoption without any previous local adoptions, the baseline value is 2.5%. Areas unsuitable for energy crops for social or environmental reasons were constrained for selection (Lovett *et al.*, 2014).

Power plant investor agents make decisions to invest in the construction and operation of power plants, that consume the energy crops, based on the expectation of the project achieving an internal rate of return, on their investment, greater than their hurdle rate (Oxera Consulting, 2011). A single delivered market price exists, which was adjusted exponentially at each year based on the level of market disequilibrium, i.e. if there is excess demand the price is increased, while if there is excess supply it is reduced. All monetary values were calculated in 2010 terms.

The model runs with a time-step of one year, starting in 2010 and continuing until 2050. A detailed description of the market emerges as the model runs proceed, including farm crop selected at a 1km^2 resolution and knowledge of the sites, sizes and technologies of the electricity power plants. This allows specific calculations of the emissions for each lifecycle stage, as the location of supply (including crop spatially specific yields), demand, and with known transport distances. Specifically, the model output helps to determine CO_2e emissions associated with the production of electricity from the energy crops, the emissions avoided from displacement of the same amount of conventional electricity generation, and the cost of subsidies provided to support market development. The total CO2e emissions abated and the total cost of subsidy were determined across the 40-year time period, allowing an average implied cost of carbon abatement to be calculated.

The model has stochastic elements, and therefore requires multiple runs to explore the distribution of output[1]. For each scenario a set of 20 runs were executed and the results of this set analysed. There are computational constraints to doing increasing numbers of runs, the results presented represents 1.93 million (SPECfp) hours, or 220 years, of CPU time on the Edinburgh Compute and Data Facility (Richards & Baker, 2008). The behaviour was determined for a range of subsidy policy scenarios, and other scenarios, chosen as part of a sensitivity analysis, detailed below.

5.3.4 Scenario and sensitivity definitions

Subsidies are available for the producers of electricity, through renewable obligation certificates. The rate of future allocation over time is not known, so alternative scenarios were examined. It was assumed that the current rate of 2.0 ROC MWh_e^{-1} would continue until 2014 and then decrease, as per the Renewables Obligation Banding Review 2013-17, to reflect the expectation of lower costs (DECC, 2011c). It was also assumed that decreases would occur over 10 years and then reach a constant level. This lower level was varied from 0.0 to 2.0 ROC MWh_e^{-1}, see Figure

[1] The model can be configured with a random number seed. If the same seed is used, the pseudo-random events follow the same sequence and repeatable results are obtained. The results presented have an automatically generated and different seed for each run.

5-3. Total revenue from sales of electricity and ROCs are shown on the secondary y-axis. The scenario with a minimum of 1.0 ROC MWh_e^{-1} is taken as the baseline scenario, which brings it more into line with the default ROC band (Ofgem, 2013b). The ROC rate is determined using the plant construction date, and held constant for the lifetime of that plant; i.e. it assumes grandfathering rights of ROC payments as per the Department of Energy and Climate Change proposals (DECC, 2011c). In addition, farmers can currently receive grants for perennial energy crops; the current rate is 50% of establishment costs (Natural_England, 2009), and this is taken as the baseline scenario. The model behaviour was determined for each of the ROC rate scenarios with establishment grant rates of 0%, 50% and 100%.

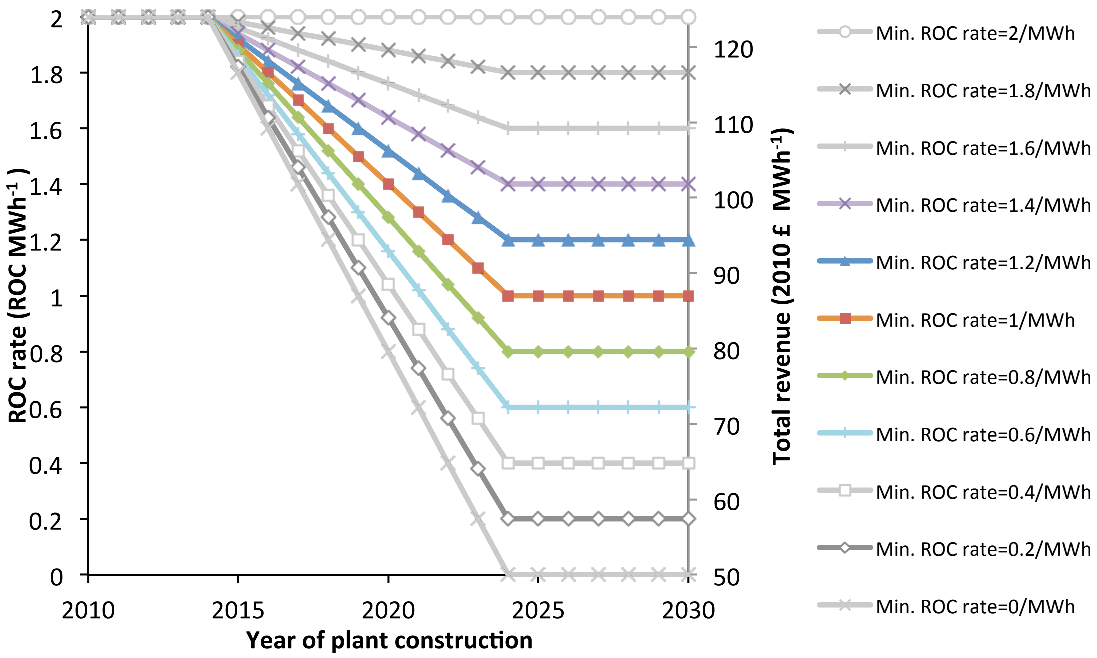


Figure 5-3: ROC rates scenarios by year of plant construction.

The parameters used for the sensitivity analysis are shown in Table 5-3. Climate scenarios are taken from the UKCP09 climate data, with the category specifying the climate forcing emission scenarios (Murphy *et al.*, 2009), and were used to estimate energy crop and conventional crop yields (Alexander *et al.*, 2014a).

Table 5-3: Parameters used for the sensitivity analysis scenarios.

Parameter	Low	Baseline	High
Initial farmer adoption rate (%)	1.25	2.5	5
Climate emissions scenario	Low[a]	Medium[a]	High[a]
Transport costs: Miscanthus/SRC willow (2010 £ odt^{-1} km^{-1})	0.135/0.085	0.27/0.17	0.54/0.34
Maximum transport distance (km)	40	80	120
Establishment grant rate (%)	0	50	100
Minimum ROC rate (ROC MWh_e^{-1})	0.6	1.0	1.6
Electricity Price (2010 £ MWh_e^{-1})	40	50	60
ROC adjustment rate: period (years)	Fast: 5	10	Slow: 20

Note:

a. Low, Medium and High climate emissions denote the climate forcing in the UKCP09 climate scenarios (Murphy *et al.*, 2009).

5.4 Results

5.4.1 Policy scenario results

As the model proceeds from 2010 to 2050 the crop selection and power plant locations vary, causing changes in the level and cost of emissions abatement. In general, as the market expands over time, the annual abatement start from a low level and increases, while the cost of carbon starts high and gradually decreases. Figure 5-4 shows the output from a sample run from the 1.0 ROC MWh_e^{-1} minimum ROC rate scenario, assuming that coal generation is displaced.

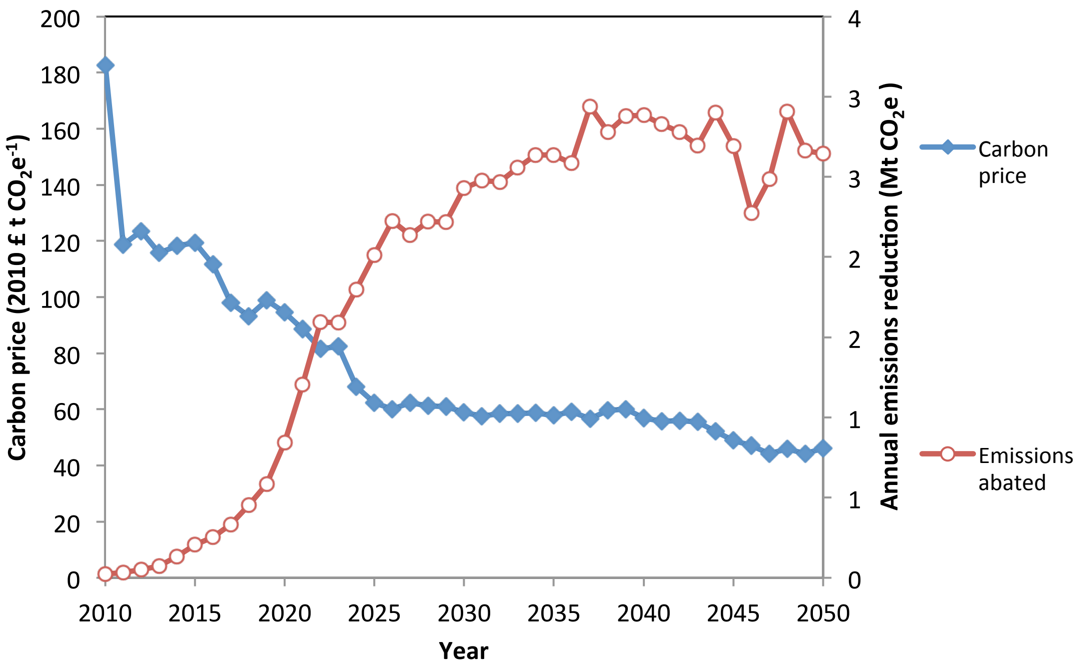


Figure 5-4: Carbon price and emissions reduction for each year from a sample run (Figure 5-6, point C) of 1.0 ROC MWh_e^{-1} minimum ROC rate scenario.

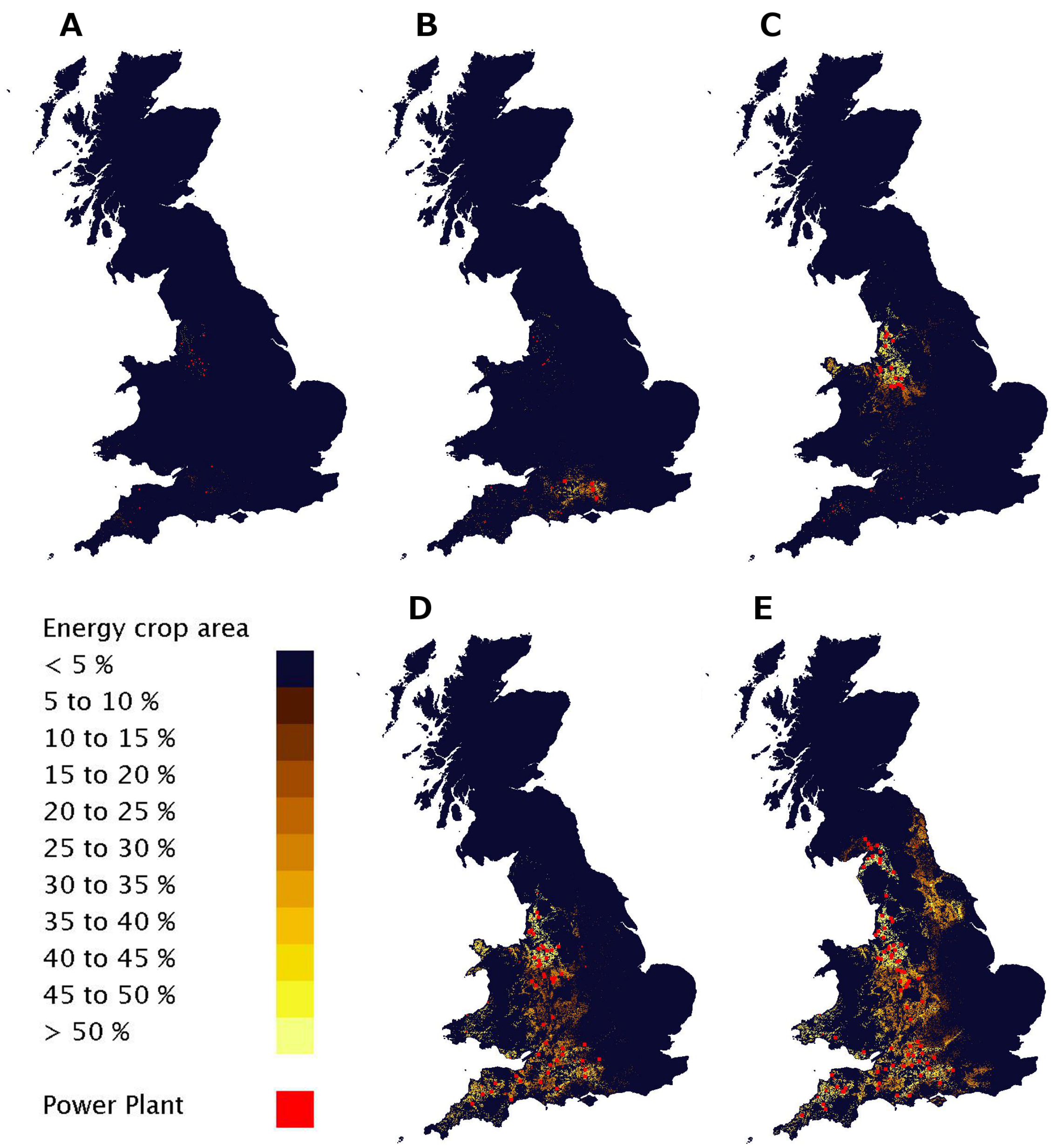


Figure 5-5: Example distributions of energy crop selection and power plant locations at 2040, A,B & C from examples 1.0 ROC MWh_e^{-1} minimum ROC rate scenario, D & E showing highest CO_2 equivalent abatement from 1.2 & 1.4 ROC MWh_e^{-1} minimum ROC rates runs.

These values were annualised over the modelled period of 2010-50, for each run, and plotted as a carbon price against an annualised CO_2e reduction. The results using an establishment grant of 50% and minimum ROC rates of 0.6-1.4 ROC MWh_e^{-1} are shown in Figure 5-6. The variability in results, within a scenario, as shown on this scatter plot, is caused by the model's stochasticity. In the 1.0 ROC MWh_e^{-1}

scenario, three distinct clusters can be observed. First, a high carbon price (~£82 t CO_2e^{-1}) and low emissions reduction potential (~0.1 Mt CO_2e), second a more moderate carbon price (~£60 t CO_2e^{-1}) and somewhat higher emissions reduction (~0.5 Mt CO_2e), and finally a similar carbon price (~£60 t CO_2e^{-1}), but greater emissions reduction (~2 Mt CO_2e). Within each cluster of results a consistent geographic pattern is observed. Figure 5-6, points A, B and C show examples of the 2040 distribution of power plants and farmers' energy crop selection from each cluster, with the corresponding case marked in Figure 5-6. The frequency of runs where a significant market is not established, Figure 5-6, point A, increases as the minimum ROC rate is reduced. At a minimum ROC rate of zero, all runs exhibit this behaviour. In scenarios with a minimum ROC rates above 1.0 ROC MWh_e^{-1}, cases occur where a more widespread market develops (Figure 5-6, point D). The prevalence of runs showing such widespread patterns increases as the subsidy rate increases. The geographic spread also increases at higher subsidy levels (Figure 5-6, point E).

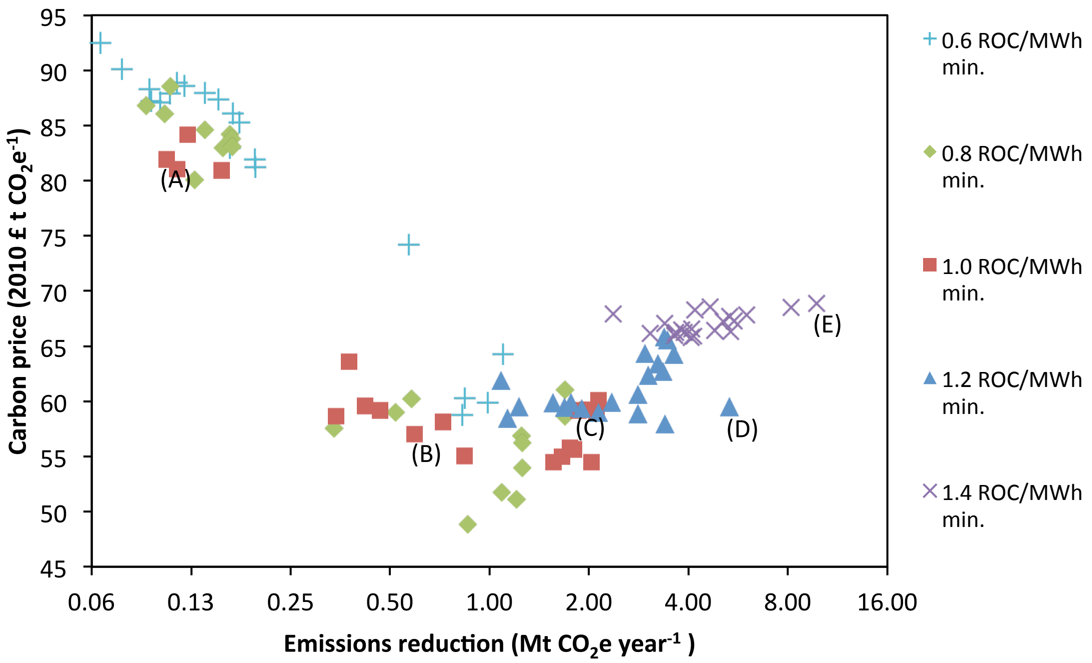


Figure 5-6: Scatter plot of individual runs with various ROC rates and 50% establishment grant showing cost of carbon abatement against emission reduction, with coal generation displaced.

The carbon prices were plotted against the mean annual emission reduction between 2010 and 2050, assuming displacement of coal, for each establishment grant rate (Figure 5-7). The resulting curves display how the level of support available to electricity generators, via ROCs, affects both the level of uptake (and hence emissions reduction), and the cost-effectiveness of the subsidy regime. As demonstrated in Figure 5-6, there is variation between each run for any set of parameters.

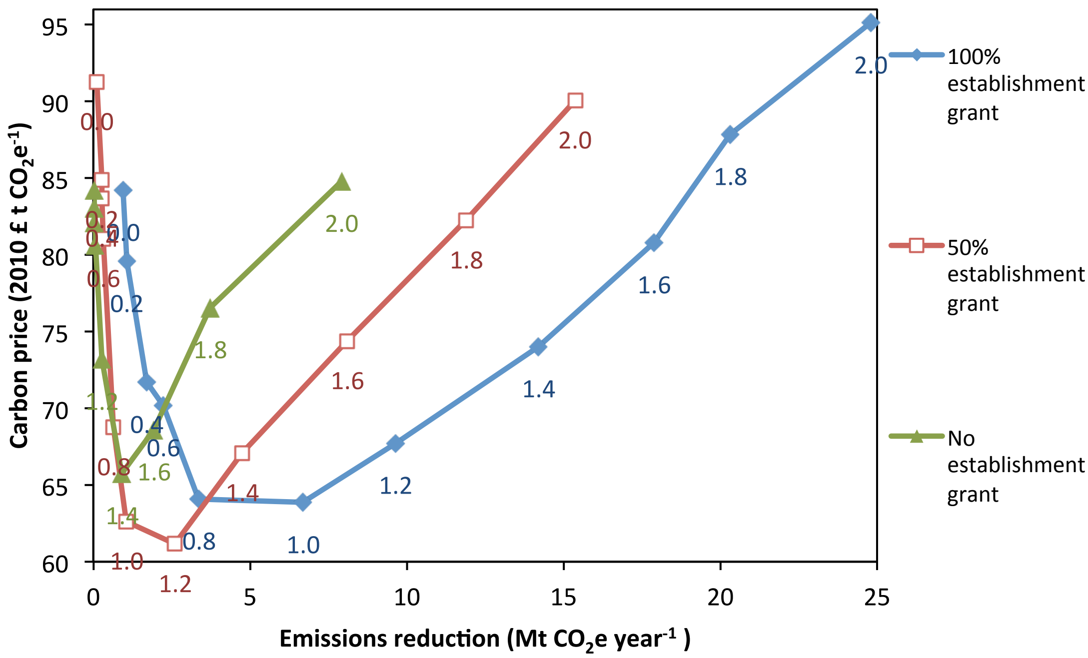


Figure 5-7: Cost of carbon abatement against annual emission reduction for various subsidy policies, assuming displacement of coal generation. The values below each point show the minimum ROC rates (ROC MWh_e^{-1}) used in that scenario.

Figure 5-8 shows the 50% establishment grant curve with error bars for the standard deviation of both emission reductions and the carbon price, using grid average electricity generation displacement. The variation in the potential behaviours (Figure 5-5 and Figure 5-6) leads to relatively a high standard deviations, particularly at lower subsidy levels.

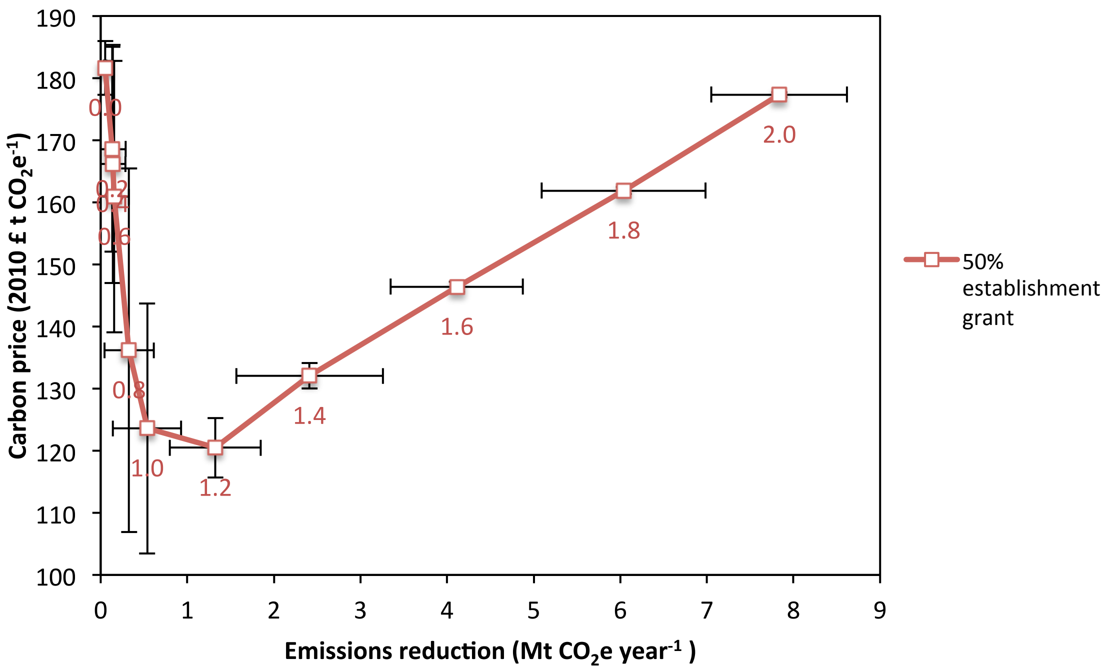


Figure 5-8: Carbon price against emission reduction, using grid average generation displacement, as minimum ROC rate is varied and 50% establishment grant, error bars showing standard deviations from a set of 20 runs for the same set of parameters.

Varying the electricity generator subsidy scenario, for a fixed establishment grant rate, produces a U-shaped curve of carbon price against emissions reduction, as shown in Figure 5-7. This indicates that there is a subsidy level that offers a maximum cost-efficiency of carbon equivalent abatement. At lower subsidy levels lower market uptake occurs, leading to lower abatement, but at a higher total subsidy cost per unit of CO_2e abated. At subsidy levels above the minimum carbon price level, there is a greater market adoption and so greater carbon abatement emerges, but the increased rate of subsidy also leads to progressively higher costs of carbon. Table 5-4 shows the points for each establishment grant scenario with the lowest carbon price, showing the emissions reduction and carbon price assuming both coal and grid average generation displacement. A comparison of the three abatement curves in Figure 5-7 shows the 50% establishment grant scenario is always at or above the no establishment grant scenario. Therefore a subsidy level with a 50% establishment grant is always at least as cost-effective at producing any level of abatement as an alternative with no establishment grant. Between the 50% and

100% establishment grant scenarios the situation is more complex. The 100% scenario has higher abatement, often at relatively small extra cost of carbon, however the lowest cost is on the 50% establishment grant curve.

The abatement curve for 50% establishment grant rate is shown in Figure 5-7 and Figure 5-8 respectively, calculated assuming coal and grid average displacement. Similarly, Table 5-4 shows both figures for the most cost-effective points for each establishment grant scenario. These show that the coal assumption has a close to doubling of the abatement potential and consequently a halving of the cost of abatement, in comparison to the grid average. The electricity generation that could be considered to be 'displaced' may change over time and the grid average figure is expected to reduce over time (DfT *et al.*, 2012). Therefore it could be argued that using current coal displacement overstates the emissions abatement. However, the rise, from 29% to 39% in 2012, of coal usage to generate the UK's electricity provides some justification for considering both options (DECC, 2013c). Also biomass electricity is dispatchable and non-intermittent, like coal, which is likely to be increasingly important within a generation mix with growing amounts of intermittent and non-dispatchable renewables, such as wind and solar.

Table 5-4: Scenario with minimum cost of CO_2e abatement for each establishment grant rate.

	Minimum ROC rate ROC MWh^{-1}	Electricity generated GWh $year^{-1}$	Biomas emissions Mt CO_2e $year^{-1}$	Emission reduction: grid Mt CO_2e $year^{-1}$	Carbon price: grid 2010 £ t CO_2e^{-1}	Emission reduction: coal Mt CO_2e $year^{-1}$	Carbon price: coal 2010 £ t CO_2e^{-1}
No establishment grant	1.4	26	0.1	0.5	130	0.9	66
50% establishment grant	1.2	73	0.2	1.3	120	2.6	61
100% establishment grant	1.0	187	0.6	3.4	126	6.7	64

The same results were used to estimate, using linear interpolation between points, the minimum ROC rate that produces a specified carbon price. These iso-carbon price points were calculate for prices at £5 CO_2e^{-1} intervals from £65 to 90 t CO_2e^{-1}, under each of the three rates of establishment grants used, and are plotted in Figure 5-9. Due to the U-shape curve (Figure 5-7) two points for each establishment grant were possible, corresponding to each side of the U, resulting in two lines for most carbon prices. At each end of the carbon prices plotted, some points were not in the range of scenarios run, giving rise to fewer points on those lines. The upper sets of lines correspond to the higher emission abatement scenarios, which have higher subsidies but an equal carbon price.

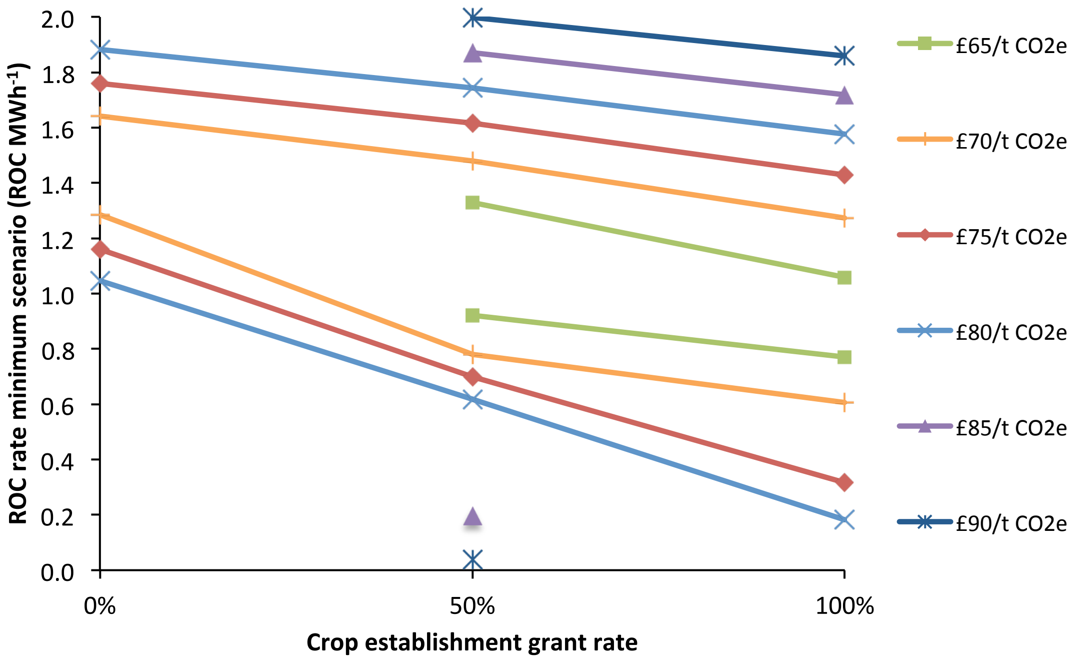


Figure 5-9: Iso-carbon price curves for carbon prices in the range £65-90 tCO_2e^{-1}, assuming displacement of coal generation.

The subsidy levels that produce iso-carbon emission abatement were determined in the same manner as for the iso-carbon price. These points were determined for emissions abatement from 0.5 Mt CO_2e to 16 CO_2e, doubling the abatement between each value; the figures are plotted in Figure 5-10. Similar to the iso-carbon price lines, some points of the highest and lowest abatements fall outside of the scenarios tested, and are therefore omitted. Figure 5-10 shows that a repeated doubling of emissions abatement can be achieved though a similar increase in subsidy levels, as the lines plotted are broadly parallel and at a constant spacing. This suggests a relatively constant relationship between changes in the subsidy levels and an exponential change in emissions abatement.

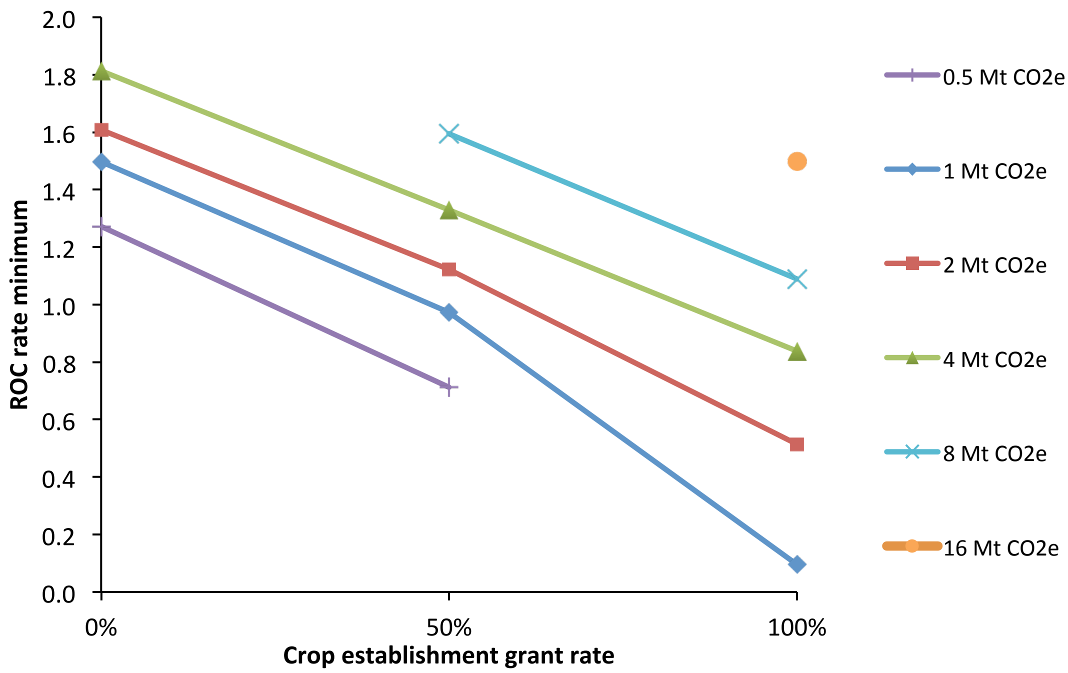


Figure 5-10: Iso-carbon emission abatement curves for carbon abatement in the range 0.5-16 Mt CO_2e^{-1}, assuming displacement of coal generation.

Figure 5-9 and Figure 5-10 show the relationship between equally desirable points, to achieve a specific carbon price or emission abatement. However, it seems highly likely that both factors would be of relevance to most policy-makers or other stakeholder. Figure 5-7 shows the relation between both carbon price and emission abatement over the range of subsidy levels tested.

5.4.2 Sensitivity analysis results

The sensitivity analysis results for the model runs using the parameter adjustments (Table 5-3), is shown in Figure 5-11.

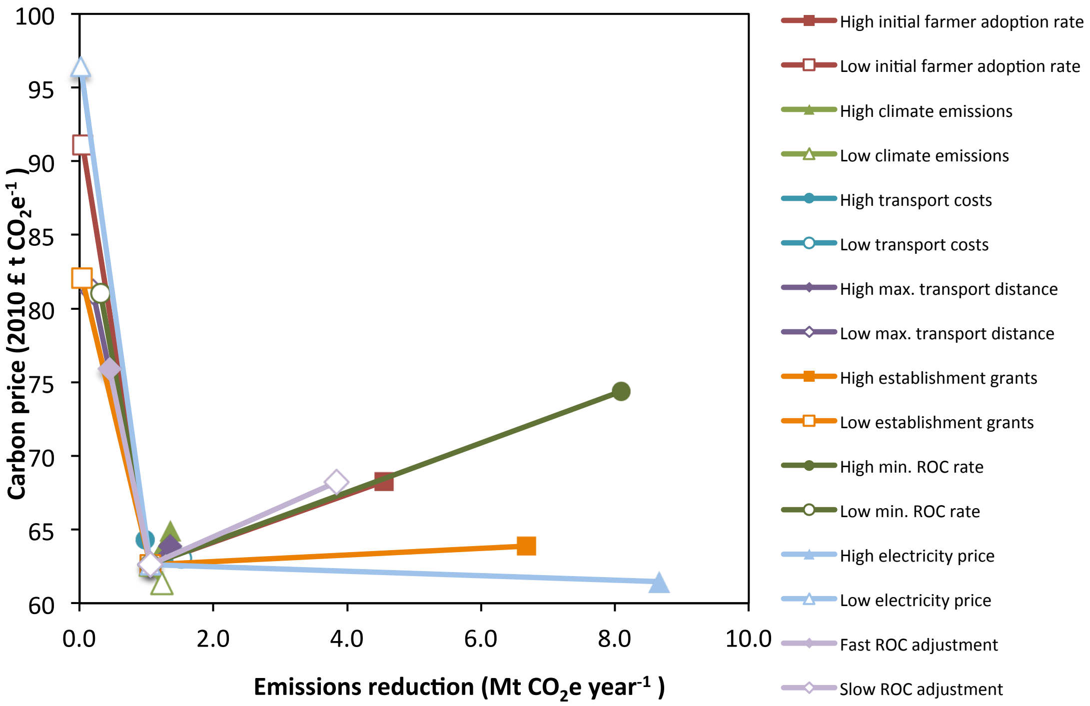


Figure 5-11: Sensitivity of carbon price and emissions reduction to a range of parameter adjustments assuming displacement of coal generation. Note: Low and High climate emissions denote the climate forcing in the UKCP09 climate scenarios (Murphy *et al.*, 2009).

Examining these results show that each scenario can broadly be put into one of three categories, according to whether it reduces the emissions abatement with an increased carbon price, has no significant effect, or increases abatement. In the cases of increased emission abatement, the carbon price either does not significantly alter (in the case of high electricity prices and high establishment grant), or shows a modest increase in carbon price (compared to the scenarios where emission abatement is reduced). Figure 5-12 highlights these classifications on the plot, and Table 5-5 tabulates the category for each scenario.

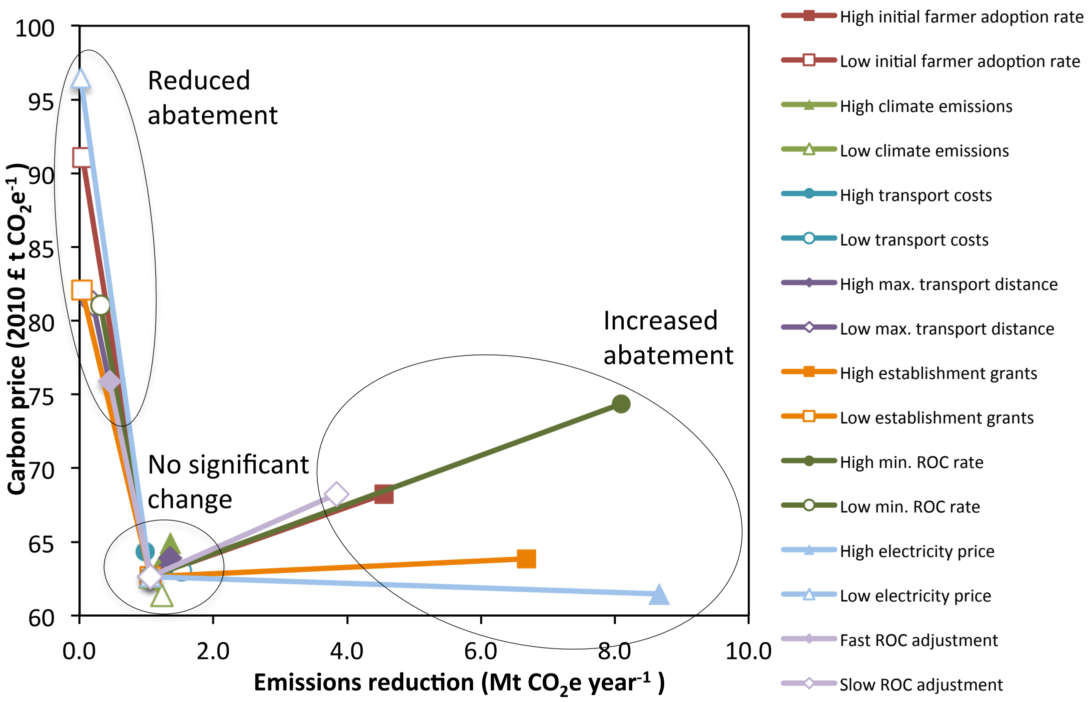


Figure 5-12: Sensitivity of carbon price and emissions reduction to a range of parameter adjustments, as per Figure 5-11, with categorisation of scenario results highlighted.

Table 5-5: Sensitivity analysis results classified into parameters that reduce abatement, have no significant impact, or increase abatement.

Parameter	Reduced abatement	No significant change	Increased abatement
Initial farmer adoption rate	Low		High
Climate emissions scenario		Low & High[a]	
Transport costs		Low & High	
Maximum transport distance	Low	High	
Establishment grant rate	Low		High
Minimum ROC rate	Low		High
Electricity Price	Low		High
ROC adjustment rate	Fast		Slow

Note:

a. Low, Medium and High climate emissions denote the climate forcing in the UKCP09 climate scenarios (Murphy *et al.*, 2009).

5.5 Discussion

The model scenarios provide a range of policy-relevant insights that are discussed further here. The reasons for the model behaviour, limitations of the approach, and opportunities for further research are also considered.

The current Energy Crop Scheme, providing farmers with 50% establishment grants, appears to fulfil an important role in stimulating market development and increasing the cost-effectiveness of carbon abatement (Figure 5-7 & Table 5-4). The current scheme closed to new applications in at the end of August 2013, and it is not clear what, if anything, will replace it. There is some expectation that this will cause the currently, albeit limited, market momentum to be lost (Lindegaard, 2013), as occurred during the previous gap in funding in 2006 (Aylott & McDermott, 2012). The results here also suggest there could be implications for the size and efficiency of the energy crop market; i.e. lower uptake, emissions abatement, and cost effectiveness, if no replacement is put in place. Even if higher subsidy levels were available to the power generators, the overall system would achieve less adoption and more costly emissions reductions without direct farmer support. The results also suggest that increasing the farmer support for energy crops, above 50% of establishment cost, increases total abatement from the market, at a relatively small increase in the carbon price A 100% establishment grant supports a six-fold increase in abatement to 6.7 Mt CO_2e for a £1 t CO_2e^{-1} increase in carbon price, compared to the 50% establishment grant. However there are many other polices, e.g. changes to single farm payments, which could be constructed to provide alternative mechanisms to stimulate farmers to adopt energy crops. Only the existing Energy Crop Scheme having been modelled and investigated. Therefore further investigations are merited. Proposals have been made by others, to providing farmers with interim, flat-rate payments per hectare over the first 5-6 years (Lindegaard, 2013), the impact of which are worth exploring.

High sensitivity is seen to the establishment grant rates. It was the only subsidy adjustment examined that encourages greater uptake and emissions abatement, while not significantly increasing the carbon price (Figure 5-11). Moving from the baseline 50% rate to 100% shows an increase of abatement from 1.1 to 6.7 Mt CO_2e year^{-1}, (with coal generation displacement), with only a marginal implied carbon price increase from £63 t CO_2e^{-1} to £64 t CO_2e^{-1}. The high sensitivity to the rate of this subsidy is a consequence of it providing support across all time periods. Similarly, Figure 5-7 shows that, at higher levels of abatement, the 100% establishment grant is more cost-effective.

Subsidising farmers directly, rather than via the biomass plants therefore appears to have potential benefits. This may be due to the distribution of margins between farmers and power plant operators; for example, in the baseline scenario, 86% of gross margin went to farmers. The adoption of energy crops by farmers requires them to overcome opportunity costs, and to make a return on the establishment investment. Since there are obvious (land) barriers to entering the supply of biomass, farmers could also be viewed as oligopolists. Supply prices, therefore, have a tendency to increase to the level where power plants are only marginally profitable. The main assumption that drives this behaviour would appear to be a single delivered market price for all market participants. Perhaps in reality, due to transactions costs, farmers might get a poorer deal. Further work, to investigating how transactions costs and market power alter the behaviours and efficiency of the market overall, is presented in Chapter Six.

Scenarios with an intermediate subsidy levels for electricity generators have been shown to produce maximum cost effectiveness (Figure 5-7 & Table 5-4). In scenarios with a low minimum ROC rate, the implied carbon abatement price is relatively high (~£90 t CO_2e^{-1}). As the support scenario increases the carbon price then falls, to between £61 tCO_2e^{-1} and £66 t CO_2e^{-1}, before rising again with further increases. For a given establishment grant rate, these minimum points represent the most cost effective subsidy level, but not the highest rate of emission abatement. Increases in the subsidy scenario gives rise to reduced failure rate and increased plant sizes, these economics of scale allow for a more efficient system to emerge. Initially, the efficiency gains are sufficient to offset the increasing subsidy cost, leading to falls in the carbon price. Eventually, the costliness of the measure overcomes any efficiency gains, creating a rising carbon price, perhaps due to reduced scope for further efficiency gains once the market is already well established. The crossover produces the minimum carbon price observed.

Where a market fails to establish, there are inefficiencies as some farmers may have planted crops and power stations have been built that may not be economic. The results show higher rates of farmers switching away from established energy crops at lower support levels. The level of negative experience of energy crops varies from 92% at 0 ROC MWh_e^{-1} to 3% at 2.0 ROC MWh_e^{-1}, due to higher prices and less susceptibility to having crops that cannot be sold or that need to be transported large distances.

Economies of scale arise as larger markets are able to support larger power plants, which have lower per MW construction costs and higher power efficiencies (Mott MacDonald, 2011). However due to availability of biomass feedstock, the model runs start by initially selecting 1MW grate plants, before potentially moving through 10MW grate plants, to then be dominated by 30MW circulating fluidised bed plants, with some 300MW circulating fluidised bed plants selected in the highest adoption scenarios. Figure 4-6 shows an example of the distribution of plant size over time. Although not represented in the model, the availability of machinery for planting and harvesting these crops would act to increase these economies of scale (Aylott & McDermott, 2012).

If all the areas suitable for energy crops were to have been selected, any further increases in subsidy could not create additional uptake, and would only result in higher subsidy costs without additional abatement. However, even in the highest support scenario, with 100% establishment grant and 2.0 ROC MWh_e^{-1}, the average maximum energy crop area obtained was 2.9 Mha, which is less than the published upper estimate of 3.63 Mha that could be grown without impinging on food production (DfT *et al.*, 2012). At these levels, higher support still encourages greater uptake and produces further emissions abatement.

Examining the behaviour of other parameters, a high sensitivity was observed in the behavioural aspects of farmers' adoptions, through the initial rate of farmers willing to consider adoption (Figure 4-2). If adoption rates were to be increased, perhaps through awareness or otherwise reducing farmers' perceived barriers, this would be expected to have a substantial effect on the rate and level of uptake. There is evidence, from both empirical and modelled results, that a spatial diffusion process of adoption is created by farmers' behaviours, leading to long time lags, of at least 20 years, before full adoption is approached (Alexander *et al.* 2013). Although some studies on the topic have been conducted (Sherrington *et al.*, 2008; Convery *et al.*, 2012), there is still considerable uncertainty in this area and scope for more work to investigate psychological barriers to adoption of novel crops, and methods to enhance awareness or increase knowledge exchange through farmer social networks, in an attempt to stimulate uptake.

Electricity prices showed the largest sensitivity of the parameters tested, with a change in electricity price of £10 MWh_e^{-1} either side of £50 MWh_e^{-1} having a dramatic impact. The sensitivity to electricity prices is greater than that to the minimum ROC rates. This is because revenue changes occur immediately and over the entire period, whereas changing the ROC rate takes effect gradually, and only reduces revenue for plants built after 2015. The reduction in the carbon price with increased electricity prices is due to this additional plant revenue not being accounted for as a subsidy.

The impact on SOC is not included in this analysis. There are potential changes in SOC due to direct land use change (dLUC), when a previous land use is displaced by growing energy crops, and indirect land use change (iLUC), where the displaced previous land use potentially shifts to an alternative area, possibly in another part of the world (Gawel & Ludwig, 2011). SOC changes from energy crop dLUC can be estimated from soil type and former land use (Hillier *et al.*, 2009). If iLUC occurs, the resulting SOC changes are uncertain, but potentially large relative to the carbon impacts of growing and using bioenergy crops (DfT *et al.*, 2012).

The UK biomass strategy suggests the theoretical maximum available land, in England and Wales, for SRC and Miscanthus, that does not impinge on food production, to be between 0.93 and 3.63 Mha (DfT *et al.*, 2012). Other land use studies suggest that large areas of land could be available, based on assumptions regarding the rate of technology development and the effect on production levels (Rounsevell *et al.*, 2006), implying that even the high adoption scenarios might be feasible in terms of land availability. All model runs fall within the upper range, and only the runs towards the highest support levels (100% establishment grant and minimum ROC rate > 1.6 ROC MWh_e^{-1}) have an average area of energy crops above the lower estimate, implying the iLUC impact may be small. Due to the nature of the model, crop selection varies over time, and therefore areas selected for energy crops may only produce for a short time period. Such reversibility makes accounting for dLUC more problematic, in part contributing to its exclusion from the analysis. Where iLUC does occur, the exclusion of both land use changes should act to offset one another.

The model represents the UK energy crop market with dedicated biomass power plants, without including other sources of demand or supply of biomass. Other sources of demand exist for biomass, e.g. existing coal fired power stations, either through co-firing or complete biomass conversion, and also other types of biomass facilities, such as dedicated biomass plants with CHP. Similarly, there is supply from imports, crop residues, wastes and forestry. The modelling simplification can be partially justified because of the current RO payment rates. There is a 0.5 ROC MWh_e^{-1} premium for dedicated biomass plant using energy crops, at current levels this equates to £18.50 MWh_e^{-1}, providing a significant incentive to solely use these crops. The current RO rates do not have a premium for energy crops usage in co-firing, providing from only 0.5 ROC MWh_e^{-1}, compared to 2.0 ROC MWh_e^{-1} for new dedicated biomass plants (Ofgem, 2013b). It is believed that at these rates, it is not economic to use energy crops for co-firing (DECC, 2012b). However EMR proposes to remove the energy crop premium and stop funding dedicated biomass power plants in favour of CHP (Aylott & McDermott, 2012), impacting on how the market may develop (Chazan, 2013). Although there may be problems finding suitable sinks for heat, particularly with the larger plants (Chazan, 2013). This potential policy change means that further work to include CHP is required, and ideally should also include other sources of biomass. Although it is difficult to quantify the impact of including these aspects on system behaviour the increase in market efficiency with higher subsidy levels appears robust and would be expected to be maintained. Adding alternative uses would reduce the overall cost of carbon if perverse incentives were avoided in the policies implemented, i.e. the economic and emissions scenarios are aligned.

5.6 Conclusions

The results suggest that directly supporting farmers, via an establishment grant, improves cost effectiveness of subsidies in reducing GHG emissions, and increases the abatement potential. A subsidy level with a 50% establishment grant is always at least as cost-effective at producing any level of abatement as an alternative with no establishment grant. Further increasing farmer support, to 100% of the establishment costs, is suggested to provide a substantial increase (six-fold) in abatement potential, for a relatively low increase in the carbon price (£1 t CO_2e^{-1}). The dedicated energy crop market may be able to achieve a cost of carbon, assuming coal generation displacement, of around £60-70 t CO_2e^{-1}, which is in line with a carbon price floor at 2030 (HM Treasury & HM Revenue & Customs, 2011). Abatement potentials are sensitive to subsidy levels, with between 2 and 10 Mt CO_2e at these carbon prices, rising up to 25 Mt CO_2e, at higher carbon prices. Using grid average emissions in place of coal as the displaced fuel approximately halves the net emissions reductions.

CHAPTER SIX

CONCLUSIONS

6.1 Main findings

This thesis has attempted to identify gaps in the existing energy and agricultural economics literature relevant to the development of energy crop supply and demand in the UK. The research attempts to draw together biophysical and socioeconomic information for use in modelling scenarios, related to a changing policy landscape.

Chapter two presents the development, validation and use of a farm-scale model, including energy crops, representing an individual farmers' crop selections under risk-aversion (Alexander & Moran, 2013). This used a set of farmer preferences (i.e. level of risk-aversion and views regarding relative energy crop risks), and specific resources (i.e. land quality and climate, producing yields on potential agricultural activities (Tallis *et al.*, 2012; Hastings *et al.*, 2014)), to determine the crop selection that maximises expected return with constant absolute risk-aversion. The results showed that the income variance from energy crops is not well correlated to conventional crop income risks, and therefore inclusion of risk reduces the energy crop price required for energy crop selection, due to benefits of a diversified portfolio of crops. However yields towards the highest of those predicted in the UK (Richter *et al.*, 2008; Aylott *et al.*, 2010) are still required to make them an optimal choice, suggesting only a small area of energy crops, within the UK, would be expected to be chosen to be grown. Model results were most sensitive to the yields of both conventional and energy crops, suggesting the need to include spatial variation in these parameters in the model. This element was included in a second stage of the analysis.

The farm-scale model was then used with spatially specific data (at a $1km^2$ resolution) to improve understanding of the total economic UK perennial energy crop supply, and the geographic and temporal distribution, driven by climate change, as described in chapter three (Alexander *et al.*, 2014a). The main inputs were yield maps for the energy crops and regional yields for conventional crops, under the range of climate change scenarios (Murphy *et al.*, 2009). These are used to configure location specific farm-scale models, which optimise for profit maximisation with risk-aversion. Areas that are unsuitable or unavailable for energy crops, due to environmental or social factors, were constrained from selection (Lovett *et al.*, 2014). Due to the high spatial resolution combined with a range of price and climate scenarios, over 10 million cases were considered. The results were maps of economic supply, assuming a homogenous farm-gate price, allowing supply cost curves for the UK market to be derived. The results showed a high degree of regional variation in supply, with different patterns for each energy crop. Using estimates of yields under climate change scenarios suggested that Miscanthus supply may increase under future climates while the opposite effect was suggested for SRC willow. The results suggest that, without increases in market prices, SRC willow is only likely to able to supply a small proportion of the anticipated perennial energy crop target. Miscanthus appears to have greater scope for supply, and its dominance may be amplified over time by the effects of climate change.

Understanding spatial supply is a necessary but insufficient condition for understanding how biomass energy scenarios might impact a range of land uses and a variety of associated ecosystem goods and services. The spatial analysis of supply implicitly assumes demand in all areas, at an exogenously supplied energy crop price, and so is unable to account for variations in transport distances or costs. Also the contingent behaviour between demand being created through investment in facilities to consume the crops and farmers choosing to grow them is not represented, nor is the behavioural aspects of farmers' adoption (i.e. diffusion of innovation). Chapter four described the ABM that was developed to provide a greater understanding of the spatial and temporal dynamics of the energy crop market and adoption scenarios (Alexander *et al.*, 2013). Results indicated that perennial energy crop supply will be between six and nine times lower than government figures, because of time lags in adoption arising from the diffusion of innovation (Rogers, 1995), and the consequential spatial diffusion process. The model simulates time lags of at least 20 years, which is supported by empirical data from an analogous oilseed rape adoption in the UK from the 1970s. This implies the need to account for time lags arising from spatial diffusion in evaluating land use change, climate change (mitigation or adaptation) or the adoption of other novel technologies.

Development of the ABM coincided with a period of upheaval in UK policy on energy, with changes being made in relation to the support policies for renewable energy and others specifically targeted at energy crops (DECC, 2013a). Accordingly the ABM was expanded to include a detailed calculation of GHG emissions balance, as presented in chapter five (Alexander *et al.*, 2014b). It was then used to calculate the total emissions abatement and total cost of subsidies that the market might provide, allowing a cost of carbon abatement to be calculated. The model was run for various policy scenarios. The results suggest that the dedicated energy crop market may be able to achieve a cost of carbon, assuming coal generation displacement, of around £60-70 t CO_2e^{-1}, which is in line with a carbon price floor at 2030 (HM Treasury & HM Revenue & Customs, 2011). Abatement potentials are sensitive to subsidy levels, with between 2 and 10 Mt CO_2e at these carbon prices, rising up to 25 Mt CO_2e, at higher carbon prices. Perhaps, the most timely policy message from the results is that they suggest maintaining the energy crop scheme, that provides farmers' establishment grants, can increase both the emissions abatement potential and cost-effectiveness. This scheme closed for new applications in August 2013, and it is unclear whether a replacement will be put in place, despite calls for a new scheme (Aylott & McDermott, 2012; Lindegaard, 2013). Another result with clear policy implications is that a minimum carbon equivalent abatement cost is seen in scenarios with an intermediate subsidy levels for electricity generators. This suggests that there may be an optimum level of support for biomass electricity to cost effectively stimulates the market to achieve emission reductions.

The production of second-generation biofuels, produced from a ligno-cellulosic feedstock, potentially provides a new market for energy crops. Despite the slower than anticipated development to commercial scale, there are now a number of pilot second-generation biofuel plants operating globally (HLPE, 2013). This provides the realistic prospect that such plants will be built in the UK in the near future. The ligno-cellulose bio-refineries have different economic and emission abatement characteristics from the biomass power plants studied here. The differences will alter the energy crop market's potential for emissions abatement and response to policy incentives. Nonetheless, there are some implications from the thesis that are likely to remain, and conclusions that can be drawn, relevant to the production of second-generation biofuels in the UK.

The addition of a new source of demand is unlikely to alter the process of farmers' adoption of novel crops, based on the spatial diffusion of uptake, resulting in long time lags. Therefore, if biofuel production from energy crops is important in the UK's future energy mix, an additional justification can be made for currently supporting electricity production from energy crops. The long time lags in achieving adoption from farmers can be overcome by establishing a market as early as possible, so that when additional demand is required (for example, for biofuel production), further and more rapid expansion is easier to achieve. The greater the size and geographic spread of the existing market, the quicker the market should be able to respond to provide additional supply. Although there is an upper limit to this conclusion, where a high proportion of suitable land has been converted, the level of uptake discussed here is not close to this limit (see Section 5.5, Page 141).

Through the stages of analysis presented here, the models have been increasing in complexity. There is also a move from the deterministic models in Chapter 2 and 3 to a stochastic model in Chapter 4 and 5. The additional complexity involved arises from the desire to expand the boundary of system being modelled, to represent additional aspects of the energy crop market, and to be able to study more of the interactions and interdependencies within it. The greatest shift is between Chapter 3 and 4, based on the desire to include demand side behaviour. An agent-based modelling approach was selected to allow the representation of the spatial aspects of a market, with heterogeneous and non-rational behaviours decision-makers, in an out-of-equilibrium market.

There is a trade-off between the simplicity and determinism of the models in the early chapters, against the more complex but descriptive models in the later ones. This could be characterised as fewer broader assumptions, moving towards a large number of narrower assumptions. Results from the later, more complex models are less immediately predicable from an examination of their inputs and as such are more able to provide new insights. Against this, the additional complexity creates issues of being able to validate the model. Although attempts at validation have been made, with some degree of success, it would be unwise to consider the model as robustly validated, and therefore the values derived must be view with some caution.

There are a number of outcomes that are independent of the precise values derived from the models. Firstly, the process of modelling such complex systems provides insights into their behaviour: for example, the interconnectedness of energy and agricultural subsidies and the key role of farmer adoption preferences are highlighted. Also, some of the conclusions appear robust over a range of parameters. For example, the U-shaped cost of carbon over electricity subsidy scenario (Figure 5-7), suggests there is a subsidy level that has a maximum cost effectiveness of carbon abatement. Also, the inclusion of a diffusion of innovation of farmer adoption both delays uptake, but also reduces the eventual level of adoption.

6.2 Changes in UK Government policy

The existing subsidy arrangements influencing the energy crop market in the UK are currently in flux. The RO scheme, supporting renewable electricity generators, ends in 2017, and the energy crops establishment grant, supporting farmers, closed for applications in August 2013. The Electricity Market Reform proposals, which are effectively the replacement for RO, have been published, and are currently in consultation (DECC, 2013a). The stated aim of the Electricity Market Reform proposals is to decarbonise energy generation in a cost-effective manner, while maintaining security of supply. It contains three main elements; a feed-in tariff using the Contract for Difference mechanism, a carbon price floor, and a capacity market. Under Contract for Difference contracts, generators revenues, from electricity and ROCs, are replaced by a single fixed price level known as the ‘strike price’. The draft Contract for Difference strike prices are claimed to have been set to be consistent with the ROCs (DECC, 2013a).

There are several specific elements of the proposed policy changes that, if implemented, have the potential to radically alter the development of the UK energy crop market. Firstly, the technologies that are eligible for support are proposed to change. New build electricity only plants would not receive support; new plants would be required to be CHP facilities to be eligible. Also, co-firing, using a proportion of biomass in existing coal fired power station, would no longer be supported, and only complete conversion to biomass from these facilities would be accepted. Secondly, the energy crop premium would be removed, this currently pays an additional 0.5 ROC MWh^{-1} (or around £18-20 MWh^{-1}) for producing electricity from energy crops, in comparison to other sources of biomass. Thirdly the terms of the support contracts are being changed. Perhaps most importantly, the contract length with RO was 20 years, but with the Contract for Difference scheme it would be reduced to 15 years in general, but with a cap, specifically for biomass contacts, to cease paying in 2027. After these contracts end, the support for renewable projects will be indirectly through the climate change levy. The climate change levy is a tax applied to the fossil fuels used to generate electricity, with a minimum level via the carbon price floor. The carbon price floor is due to be £70 Mt CO_2e^{-1} in 2030, which is expected to increased wholesale electricity price from £50 MWh_e^{-1} to £70 MWh_e^{-1} by 2030 (National Grid, 2013), in 2012 terms. Fourthly, and finally, the Energy Crop Scheme, supporting farmers with establishment grants, closed to applications in August 2013, and it is unclear whether a replacement will be put in place.

In an attempt to communicate the findings of this research, two policy notes have been written for policy-makers (Alexander, 2014; Alexander & Moran, 2014). Further direct communication with individuals within DECC and DEFRA has been attempted, but without much success. It is unfortunate timing that the establishment grant scheme for farmers ended just as some evidence became available suggesting the important role that it plays in the uptake of the market.

6.3 Potential for further work

A number of modelling assumptions regarding the market have been at least partially invalidated by the previously mentioned shifts in UK Government policy (DECC, 2013a). Firstly, the exclusion of support for dedicated power only generation, in favour of CHP plants, means that CHP plants need to be represented within the model. This creates issues with regard to where the heat can be used, as well as the need to assess parameters for costs and efficiencies. Secondly, removal of the energy crop premium also means that the incentive for plant to consume only energy crops has been removed. Therefore energy crop will compete more with other sources of biomass for usage by power generators. As a result it would be advantageous to represent the availability of these other biomass sources.

This is a complex system that has the potential to produce a range of benefits (e.g. renewable energy and carbon abatement), as well as disbenefits (e.g. land-use change, and competition with food production and water resources). The policy uncertainty acts to increase the need for greater scientific understanding of these trade-offs and analysis on what measures are appropriate and cost-effective. This is further heighted by the current public and political interest in the energy system, and associated costs and benefits.

There is significant further scope to increase understanding of how the UK energy crop market, and the bioenergy market more generally, could be influenced by policy, and what role the market could play in meeting renewable energy and emissions policy targets. To assist in accomplishing such a task, the model presented could be updated to reflect the proposed changes to the UK Government's energy policies, for example under Electricity Market Reform. In addition, it would be advantageous to expand the diversity of both the technologies that have demand for biomass, and the sources of producing that biomass, represented in the model. On the supply side, other domestic sources of biomass could be included, e.g. short-rotation forestry, agricultural and forestry residues, as well as consideration of biomass from imported sources. Imports could be included by assuming a supply curve for each port would allow imports, or more complex representations of imports could be attempted including global trade approaches. It should also be possible to apply the existing model to other countries or regions, given yield maps of the crops that could be selected. In addition to the insights provided into those markets, applying the model to other geographic areas would also help to develop and validate the model.

The additional technologies that could be included within an analysis of the UK biomass market would include combined-heat and power plants, pellet manufacturing, existing coal power stations either co-firing or fully converting to biomass and bio-refineries. The construction of lignocellulose bio-refineries, producing second-generation biofuel, is likely to create a substantial shift in the economics and perhaps perception of biomass. This is a realistic prospect once the construction of commercial scale plants has become a more proven technology in other countries. Modelling of second-generation biofuel plants, to investigate the impact on the economics of the biomass market and the GHG emission abatement potential would be an interesting topic for research, and is likely to be policy relevant.

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APPENDIX I

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APPENDIX II

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APPENDIX III

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